A Version of Watershed Algorithm for Color Image Segmentation
Md. Habibur Rahman and Md. Rafiquil Islam

Abstract—Finding of semantic regions is the main objective of segmentation for image understanding. Automatic image segmentation is one of the major difficulties in the field of image processing. The watershed algorithm has some problems, like over segmentation, sensitive to noise, and high computational complexity. To overcome these problems, we have proposed a Modified Watershed (MWS) algorithm for color image segmentation by adaptively selecting threshold and masking mechanism over each color channel before combining the segmentation from each channel into the final one. For qualitative performance, proposed modified watershed algorithm performance compare with four modified watershed algorithms. For quantitative verification, proposed MWS method with two modified watershed algorithms in terms of executing times. The presented method have compared with FCM, RG and HKM algorithms for color image Segmentation in 10 different classes of images with respect to PSNR, MSE, PSNR_{RGB}, QM and RFSIM. It is worth noticing that our proposed approach is low computational complexity. According to the visual and quantitative verifications, the proposed MWS algorithm is better than others three algorithms on the segmentation of color image.

Keywords: Color Image Segmentation, Watershed Transform, PSNR, MSE, PSNR_{RGB}, RFSM, CQM, YUV Transformation.

1. Introduction

Image Segmentation is a process to divide the digital image into homogeneous and different meaningful regions. It is a process to separate the desired objects from the original background image [1]. Image segmentation and grouping the similar visual objects has based on some measurements such as grey level, color, intensity, texture, shape, depth or motion from the image. It plays a key role in the fields of image processing, medical research, remote sensing image, pattern recognition, image visualization, image retrieval, content-based image compression, computer vision and graphic applications. The role of image segmentation is vital in most tasks demanding image analysis [2] [3]. Segmentation is the first stage in any effort to analyze or interpret an image automatically.

It bridges the gap between low-level image processing and high-level image processing. Finding semantic regions is the main objective of segmentation for image understanding. Image segmentation technique can be broadly classified into the following categories as pixel-oriented, region-oriented, clustering-oriented, contour-oriented, model-oriented, histogram thresholding, markov random field, edge-based, color-oriented and hybrid [4]. Usually, Segmentation evaluation methods can be divided into two categories such as supervised and unsupervised. Unsupervised methods are fully automatic and segment the regions in feature space with high density [5]. Though, numerous of approaches have been offered to segment images, no one could always work well for different kind of images. For example, Edge-based techniques cannot achieve enclosed region boundaries, while the region-oriented algorithm may lead to over-segmentation or under-segmentation difficulties. To achieve satisfying results by applying different optimization techniques for image segmentation, commonly researchers may need to use a user interaction process or a very time consuming method [6].

The main drawback of watershed transform is over-segmentation, sensitive to noise and high computation complexity those make it unsuitable for real-time process [7]. To overcome over-segmentation problem, the improved techniques can be divided into two main categories, e.g. post-processing and pre-processing approaches. In post-processing methods, it reduces over-segmentation by integrating homogenous regions after watershed transform, but it significantly increases the computational complexity. It is similar to the hybrid method than modified watershed algorithm. Basically it doesn’t solve over-segmentation problem [8]. In pre-processing approaches, it commonly recognized by some feature detection algorithm and marker-based watershed methods. The feature detection contains local minima, homogeneous regions, texture homogeneous regions etc. Though, it is hard to extract markers relative to objects accurately. Fundamentally, it is a nice idea to solve over-segmentation by marker-based watershed segmentation by comparing local minima depth with a constant threshold [9]. But it has particular serious disadvantages as well, where color gradient is calculated in each color channel independently, ignoring the high correlation among the R, G, and B components. There haven’t proposed an advisable algorithm for threshold selection [7].
To overcome these difficulties, we have offered a modified watershed algorithm by applying adaptively selecting threshold and masking operation for color image segmentation. Firstly, we extract RGB image into three color channels. The N-Dimensional convolution function has used for smoothing image. Morphological image processing operation has been used in our approach.

For experimental evaluations, we have compared our proposed MWS algorithm with Fuzzy C-Means (FCM), Region Growing (RG) and Hill-climbing with K-Means (HKM) along with different classes of images. We have done experiments on color image segmentation to compare the performance of our proposed MWS algorithm along with three different algorithms with respect to PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error), PSNR<sub>RGB</sub>, RFSIM (Riesz-transform based Feature Similarity Metric) and Color Image Quality Measure (CQM) based on reversible YUV color transformation.

2. Review of Watershed Algorithm

The watershed transformation is a powerful tool for image segmentation based on well-known mathematical morphology-based approach [10]. Watershed transform has concerned with great attention in recent years as an efficient morphological image segmentation tool. It treat as a gray-scale image as a 3D visualization of images correspond to geographic altitude, separable regions correspond to water basin, and edges between two adjacent regions corresponds to water lines. It is similar to region-based approach; it begins the growing process from every regional minimum point, each of which creates a single region after the transform. Watershed algorithm combines both the discontinuity and similarity properties successfully [6].

The fundamental idea underlying this method comes from geography: it is that of a topographic relief which is flooded by water, watershed lines being the divide lines of the domains of attraction of rain falling over the region. Research study by Vincent and Soille [11] proposed immersion simulation technique based on a FIFO queue to implement the watershed segmentation, which has been proven to be the fastest and most accurate one. If the gray level of an image is considered as the height of the topographic surface then the watershed can be considered as immersing the image surface in water. Assuming there are holes pierced in each local minima, catchment basins will fill up with water starting at these local minima, and dams are built at points where water coming from different basins would meet. When the water level has touched the highest peak in the surface, the process is stopped. The surface is separated into catchment basins associated with each minimum by dams. At the end of the process, the union of all those dams creates the watershed ridge edge lines, form closed region boundaries (Figure 1) [12] [13].

Figure 1: Watershed Transform

The benefits of watershed segmentation are threefold. Initially, the consequences are connected regions with enclosed boundaries of single pixel wide, different from the traditional edge-based methods generating disconnected contours. Next, the region contours adhere well to the real object boundaries. Moreover, the combination of regions produced by watershed segmentation is equal to the entire image [6].

C. Zhang [14] proposed a marked extraction based on adaptive color image segmentation algorithm to improve the watershed algorithm, the traditional marker for the lack of extraction methods, many consider the minimum characteristics of properties, and set the adaptive threshold. Their proposed method performs better than original watershed algorithm, with a strong anti-noise performance. Several approaches exist to solve the over-segmentation problem, such as integrated the K-Means clustering with marker controlled watershed segmentation[15], integrating watershed with region merging algorithm [16], watershed based on gradient modification and hierarchical region merging algorithms[17], combined marker-based watershed and region merger[18], marker-controlled watershed crown segmentation [19], morphological gradient applied to new active contour model [20], marker-based watershed algorithm [21] and interactive segmentation by matching attributed relational graphs are based on watershed, graph cuts, shortest paths (geodesic) and random walker [1].

3. Modified Watershed Algorithm

In this section, we have proposed a modified method for color image segmentation. It can quickly calculate the every region of the watershed segmentation. It is improved by considering adaptively selecting threshold, adaptive masking operation, local minimum information and convolution function for smoothing the image. The image segmentation process is described following step provided below. The flowchart of the proposed methodology provided in Figure 2.
Step 1. We have used an RGB image as input color image. The original image is extracted into individual red (R), green (G), and blue (B) color channels as shown in Figure 3.

![Figure 3: Extracted Original image into R, G and B channels](image)

Each color channel is normalized zero to one. The image normalization process is computed by the Eq. 1.

\[ N = \frac{I - \min(I)}{\max(I) - \min(I)} \]  

Where, the extracted three color channels represented by I. Image normalization is denoted by N.

Step 2. To determine the adaptive threshold, we have used a dynamic threshold selection process \((T_1, T_2)\) by Eq. 2 and Eq. 3 based on Gray-threshold function.

\[ T_1 = G_i(N) \]  
\[ T_2 = G_i(N \cdot T_1) \]  

Where, Gray threshold is calculated by \(G_i\).

Step 3. We have generated N-dimensional grid space (NDGRID). It is required for N-dimensional convolution (convn) function. We have applied image normalization (N) and NDGRID into N-dimensional Convolution for smoothing image on three color channels as given in Figure 4. It is a simple, non-iterative scheme for edge-preserving smoothing filter. The N-dimensional convolution is represented by \(C_n\). Where \(n\) is the channel number.

![Figure 4: N-dimensional Convolution Filtering](image)

Step 4. The masking operations are divided into two stages: cell and nucleus making. The better cell-mask and nucleus-mask value are determined by Eq. 4 and Eq. 5. The adaptive masking operations are used image normalization (N) and adaptive thresholding \((T_1, T_2)\) on the R, G and B color channels as shown in Figure 5.

\[ M_1 = N \cdot T_1 \]  
\[ M_2 = N \cdot T_2 \]  

Where, cell-mask and nucleus-mask are denoted by \(M_1\) and \(M_2\) respectively.

![Figure 5: Adaptive Masking operation on three channels](image)

Step 5. An image can have several regional maxima or minima but only one global maxima or minima. We have used Impose Minima \((\text{imimposemin})\) to create new minima in the mask image at certain desired location by adaptively selecting threshold operation \((T_1, T_2)\) for morphological reconstruction to eliminate all minima from the image except the minima we specified. For morphological processing, we have applied Impose Minima \((\text{imimposemin})\) function to create morphological process image \(F_n\) using nucleus-masking \((M_2)\) and adaptive mask image on three color channels as shown in Figure 6.

![Figure 6: Morphological Processing on three color channels](image)

Step 6. The watershed transform algorithm are applied based on the morphological processing image on R, G and B color channels as shown in Figure 7. It can be represented by \(W_n\).
Step 7. The pixel labeling process is started on each color channel after watershed algorithm. To determine a background image, we have used \( W_n \sim M_1 \) = 0 functions. \( L_n = BWLABEL \left( W_n \right) \) function, returns a matrix \( L_n \), containing the labels for the connected objects in the 2-D binary image on each color channel. The elements of \( L_n \) are integer values greater than or equal to 0. It labels foreground objects in the binary image. The pixels labeled 0 (\( L_n = 0 \)) are the background image. The pixels labeled 1 make up one object; the pixels labeled 2 make up a second object, and so on.

Step 8. In post processing operation, we have converted R, G and B label image into an RGB image using \( P_n = Label2rgb \left( L_n \right) \) for the purpose of visualizing the labeled regions as shown in Figure 8. Where, \( n \) is the number of channel.

Step 9. The three color channels (\( P_n \)) are combined for final segmentation as shown in Figure 9.

We have applied canny edge detection method to detect enclosed region boundary and remove all small object from the combined three color channels as shown in Figure 10.

Figure 7: Watershed Transform on three color channels

Figure 8: Post processing operation on three channels

Figure 9: Final Segmentation

Figure 10: Extracted object

Figure 11: Superimposed on original image

a. Quality Evaluation Metrics

We have used four different image quality assessments (IQA) metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), Color Image Quality Measure (CQM) and Riesz-transform based Feature Similarity Metric (RFSIM). The PSNR computes the peak signal-to-noise ratio, given in decibels (dB), between two images (original and segmented image). The MSE represents the cumulative squared error between the segmented and the original image, whereas PSNR represents a measure of the peak error. The higher PSNR shows that the segmented image is closer to the original image. For color image, different methods exist for calculating the peak signal-to-noise ratio (PSNR). Usually, PSNR and MSE are used as image quality evaluation function or quality metrics. PSNR and MSE are used in several studies to evaluate the performance of presented techniques [24][25]. There are several measurement technique used for evaluating image quality such as Structural Similarity Index Metric (SSIM) [26], multi-scale extension of SSIM (MS-SSIM) [27] and Riesz-transform based Feature Similarity Metric (RFSIM) [28].

Numerous efforts have taken into improvement of image quality measures that take benefit of standard characteristics of the Human Vision System (HVS). We have applied Color Image Quality Measure (CQM) to estimate our proposed method along with others algorithms. It follows a strategy of changing the implementation way of the PSNR. It is based on two main parts. Firstly, a reversible color transformation is
realized from RGB to YUV by using an original color image and its segmented color image. A color transformation is initially used as a preprocessing step before intra-component coding in any image segmentation application for color images. In YUV transformation, Y is the luminance component while U and V are the blue-difference and red-difference components of the YUV, respectively [29].

A-1. Peak Signal to Noise Ratio (PSNR)

PSNR is the value of the noisy image with respect to that of the original image. PSNR of the color texture based image segmented can be calculated by using the Eq. 6. PSNR range between [0, 1), the higher PSNR value indicates better image quality [24].

\[ PSNR(GI, SI) = 10 \log_{10} \frac{s^2}{MSE(GI, SI)} \]  

(6)

A-2. Mean Square Error (MSE)

MSE is the average squared difference between an original image and a segmented image. Mean Square Error (MSE) is calculated pixel-by-pixel by adding up the squared differences of all the pixels and dividing by the total pixel count [24]. MSE of the segmented image can be calculated by using the Eq. 7. MSE ranges between [0, 1], lower is better.

\[ MSE(GI, SI) = \frac{\sum_{i=0}^{N-1} \sum_{j=0}^{M-1} (GI(i, j) - SI(i, j))^2}{MN} \]  

(7)

In Eq. 6, S is the maximum fluctuation in the input image data type. N and M are the number of rows and columns in the input images, respectively. Where GI is the original image, SI is the segmented image of size N x M. For instance, if the input image has a double-precision floating-point data type, then S is 1. If it has an 8-bit unsigned integer data type, S is 255, etc.

A-3. YUV Transformation and Color Image Quality Measure (CQM)

Our chosen color transformation is from RGB to YUV. We estimate CQM based on offered approach by Y. Yilman and D. Erturk [29]. The CQM ranges between [0, 1), CQM value is always higher than PSNR<sub>RGB</sub> value. An estimated Reversible YUV Color Transformation (RCT) that is created from the JPEG2000 standard and called as RCT is given in Eq. 8 [30][31].

\[
\begin{align*}
Y &= R + 2G + B \\
U &= R - G \\
V &= B - G
\end{align*}
\]

(8)

\[
\begin{align*}
R &= U + G \\
G &= Y - \frac{U + V}{4} \\
B &= V + G
\end{align*}
\]

Primarily, an original RGB image and its segmented image are transformed to the YUV (RCT) images by using the RCT equation (7). Next, the PSNR quality of each YUV (RCT) channel (Y, U and V) is calculated separately. Finally, CQM value is calculated using the Eq. 9 as shown below.

\[ CQM = (PSNR_y \times R_w) + \left( \frac{PSNR_u + PSNR_v}{2} \right) \times C_w \]  

(9)

Where, the weighted luminance quality measure \( PSNR_y \times R_w \) and weighted color quality measure \( \left( \frac{PSNR_u + PSNR_v}{2} \right) \times C_w \) components. \( C_w \) and \( R_w \) mean the weights on the human perception of these cone and rod sensors. \( C_w = 0.0551 \) and \( R_w = 0.9449 \).

A-4. Riesz-transform based Feature Similarity Metric

We have used a novel feature based Image quality assessment (IQA) model, namely Riesz-transform based Feature Similarity Metric (RFSIM) based on the human vision system (HVS) perceives an image mainly according to its low-level features proposed by L. Zhang and others [28]. RFSIM range between [0, 1), the higher RFSIM value indicates better image quality. It is calculated by comparing the feature maps at key locations marked by a feature mask between two images. Assume that we are going to compute the similarity between two images f and g. Here, we denote by M1 the result of edge detection performed on f and M2 the result of edge detection on g. Then, the feature mask is defined as Eq. 10.

\[ M = M_1 \oplus M_2 \]  

(10)

Where \( \oplus \) is the logical “OR” operation. In this section, the 1st-order and the 2nd-order Riesz transforms can extract some low-level image features effectively and efficiently in a unified theoretic framework. The similarity between two feature maps \( f_i \) (i = 1-5) and \( g_i \) at the corresponding location (x, y) is defined as the Hilbert transform of a 1-D function in Eq. 11.

\[ d_i(x, y) = \frac{2f_i(x, y) - g_i(x, y) + c}{f_i^2(x, y) + g_i^2(x, y) + c} \]  

(11)

Where, \( c \) is a small constant value. This naturally leads to the following formula to define the similarity between the feature maps \( f_i \) and \( g_i \) by considering only the key locations marked by mask M and Hilbert transform of a 2-D function provided in Eq. 12.

\[ D_i = \frac{\sum_{x, y} d_i(x, y) \cdot M(x, y)}{\sum_{x, y} M(x, y)} \]  

(12)

Then, we compute the RFSIM index between f and g image as Eq. 13 shown below.

\[ RFSIM = \prod_{i=1}^{5} D_i \]  

(13)
4. Result Analysis

The experimental results achieved by the offered color image segmentation technique. The experiment is implemented in MATLAB 7.12.0 an Intel (R) Core (TM) i7-2670QM 2.20GHz machine running on 4GB RAM, Windows 7 platform using the image processing toolbox. To evaluate the performance of four different algorithms, an image database consisting of 100 images was used in this study. Most of the color image obtained from Berkeley segmentation database [32] where size of image is 481x321. In order to facilitate performance comparison of quantitative displays of the results, as in [33] [34], all color images are normalized to have the longest side equals to 320 pixels in all the experiments.

a. Visual Verification

For visual verification in Appendix A (Figure 18-19) provides a comparative performance of our proposed MWS method with four modified watershed methods [7] [8] [9] [16]. Similarly, we have compared and analyzed the performance of Fuzzy C-Means (FCM), Region Growing (RG), Hill-climbing with K-Means (HKM) and the offered Modified Watershed (MWS) algorithms on color image segmentation with 10 different classes of images as shown Appendix A (Figure 20). The 10 different images are namely “Aeroplane”, “Boat”, “Building”, “Butterfly”, “Deer”, “Duck”, “Hand”, “Fish”, “Mountain” and “Tiger”. Appendix A gives out some examples of color image segmentation results by Fuzzy C-Means (FCM), Region Growing (RG), Hill-climbing combined K-Means (HKM) and the proposed Modified Watershed (MWS) algorithms for visual verification.

b. Quantitative Verification

We quantitatively compare the performance of our offered modified watershed (MWS) algorithm, Fuzzy C-Means (FCM), Hill-climbing with K-means (HKM), and Region Growing (RG) algorithms with respect to Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Riesz-transform based Feature Similarity Metric (RFSIM), Color Image Quality Measure (CQM) based on reversible YUV color transformation. CQM measures depend on a unique feature of the human eye response to the luminance and color [29]. We will compare the performance of the proposed method with marker-based watershed and Modified watershed Method [7]. In Figure 19 are segmentation results of noiseless image “Hand” and Noisy Color image “Deer”, whose sizes are both 481x321. The executing time by each method is showed in Table 1.

We can see that our proposed algorithm perform in case of noiseless and noisy color image. We also compare the performance of our method with respect to five quality evaluation metrics such as PSNR, MSE, PSNR_RGB, CQM and RFSIM etc.

The MWS algorithm is more effective in the color image segmentation, and solves the problem of the over-segmentation generated by the watershed transform. In addition, as seen in Figure 12 compare the average running times of different approaches. MWS and the FCM are the fastest implementations, where RG and HKM are the comparatively slowest ones. The proposed MWS method is superior to the competing algorithms in efficiency.

Table 1: Executing Time (Second)

<table>
<thead>
<tr>
<th>Method</th>
<th>Deer</th>
<th>Hand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marker-based [9]</td>
<td>7</td>
<td>2.6</td>
</tr>
<tr>
<td>Method [7]</td>
<td>3.3</td>
<td>1.3</td>
</tr>
<tr>
<td>Proposed</td>
<td>0.75</td>
<td>0.61</td>
</tr>
</tbody>
</table>

The average performance of PSNR, MSE, PSNR_RGB, RFSIM and CQM for the image segmentation of FCM, RG, HKM and proposed Modified Watershed algorithms are given in Table 2.

Table 2: Average Performance of four algorithms using PSNR, MSE, PSNR_RGB, CQM and RFSIM

<table>
<thead>
<tr>
<th>Metrics (dB)</th>
<th>FCM</th>
<th>RG</th>
<th>HKM</th>
<th>MWS</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSNR</td>
<td>55.85</td>
<td>52.38</td>
<td>55.00</td>
<td>58.32</td>
</tr>
<tr>
<td>MSE</td>
<td>0.21</td>
<td>0.40</td>
<td>0.22</td>
<td>0.12</td>
</tr>
<tr>
<td>PSNR_RGB</td>
<td>8.31</td>
<td>6.00</td>
<td>7.02</td>
<td>10.57</td>
</tr>
<tr>
<td>CQM</td>
<td>15.51</td>
<td>29.71</td>
<td>26.03</td>
<td>17.59</td>
</tr>
<tr>
<td>RFSIM</td>
<td>-3.4E-4</td>
<td>0.0011</td>
<td>-0.0001</td>
<td>0.0356</td>
</tr>
</tbody>
</table>
From these quantitative results in Figure 13-14 and we can see that our method performs better than other three methods in terms of most indices.

Quantitatively evaluating the performance of a general segmentation method is still difficult. From Figure 15 shows that our proposed method is performing better than others.

From Figure 15-16, we can figure out PSNR_{RGB} always lower than CQM. Further, without systematic arguments, CQM measures couldn’t become a standard indicator of human visual system (HVS) segmentation in human perception. In our study we can noticed that CQM does not able to define the performance difference among segmentation algorithms.

From the Figure 17, we can notice that our proposed MWS algorithm is outperforms to the others.

This conclusion is also pointed out in our study that traditional PSNR, MSE, PNSR_{RGB} and RFSIM provide performance difference among FCM, RG, HKM and proposed MWS algorithms. Recently, researchers tend to apply all these complementary measures in order to quantify the performance of their segmentation methods. In future research on image segmentation, we expect a more standard performance measure which could well reflect the difference between segmentation results.

5. Conclusions

Automatic image segmentation is one of the major difficulties in the field of image processing. A modified color image segmentation algorithm is offered by adaptively selecting threshold and masking operation with watershed algorithm. We have compared our proposed MWS algorithm with two
other modified watershed algorithms. Similarly, we have computed the performance of our MWS method with FCM, RG and HKM segmentation techniques for color image Segmentation in 10 different classes of images with respect to PSNR, MSE, RFSIM, PSNR_Ren and CQM. The results achieved using our technique ensure accuracy and quality of the image in 10 different classes of images. We have noticed that qualitatively our proposed MWS algorithm perform better than four other modified watershed algorithms. Accordingly, the proposed modified watershed (MWS) method can enhance the image segmentation performance. Likewise, it is worth noticing that our proposed MWS approach is less computational complexity, which makes it appropriate for real-time application. According to the quantitative verification, the proposed watershed algorithm is better than others two modified algorithms on the segmentation of color images. We assume that our works could give new insights to people who are interested in image segmentation. Our future work will be focus on more robust algorithm for video image segmentation.

REFERENCES


Appendix A: Comparison chart of color image segmentation results

![Original Image](image1.png) ![Method [16]](image2.png) ![Proposed Method](image3.png)

![Original Image](image4.png) ![Method [14]](image5.png) ![Proposed Method](image6.png)

*Figure 18: Comparison chart of image segmentation results*

![Original Image](image7.png) ![Marker-based [9]](image8.png) ![Method [7]](image9.png) ![Proposed Method](image10.png)

*Figure 19: Comparison chart of image segmentation results*
Figure 20: Color image segmentation by FCM, RG, HKM and proposed MWS algorithms
Md. Habibur Rahman received B.Sc. degree in Computer Science and Engineering (CSE) from East West University (EWU), Dhaka, Bangladesh in 2009 and currently he is doing MS in Computer Science in American International University-Bangladesh (AIUB). He has published several papers in referred international conference proceedings. His present research interest includes Image Processing, Wireless and Mobile Networks, Mobile Ad-hoc Network, Network Security, Cloud Computing and computer Networks.

Prof. Dr. Md. Rafiquel Islam obtained MS securing first class with honors in Computer Engineering from Azerbaijan Polytechnic Institute (Azerbaijan Technical University) in 1987 and Ph.D. in Computer Science from Technological University of Malaysia (UTM) in 1999. He did Post Doctoral research in Japan Advanced Institute of Science and Technology (JAIST) as a JSPS fellow in 2001. He worked as a Professor, Head of Computer Science and Engineering Discipline and Dean of Science, Engineering & Technology School of Khulna University. Currently he is working as Professor in Computer Science Department of American International University-Bangladesh (AIUB). He has published more than 70 papers in National and International Journals as well as in referred International Conference Proceedings. His research interest includes Design and Analysis of Algorithm in the area of Information Security, Image Processing, Grid Computing, Cloud Computing, Bio-informatics, Information Retrieval etc.