

# Optimization of Shadow Detection and Removal using Multilevel Thresholds and Improved Artificial Bee Colony Algorithm



Rakesh Kumar Das , Madhu Shandilya

*Abstract-Shadow Detection and removal from images is a challenging task in visual surveillance and computer vision applications. The appearance of shadows creates severe problems. There are various methods already exists but scope in this area is wide and open. In this paper, Optimization of Shadow Detection and Removal using Improved Artificial Bee Colony Algorithm (IABC) is proposed. The proposed method uses edge map, multilevel thresholds, masking, boundaries evaluation and, IABC algorithm. First data pre-processing is applied to find the correlation between the pixels then three level low, medium and high value of thresholds and the corresponding value of masking and boundaries are calculated to accurately differentiate pixels as foreground. The edge response, curvature, gradient are applied to find the true location of boundaries. Finally, IABC has been applied for detecting the shadow and median filter is used to remove the shadow. The results show improvement as compared to other existing methods.*

*Index Terms – Masking, shadow removal, artificial bee colony, foreground, thresholds, median filter, boundary evaluation.*

## I. INTRODUCTION

Shadows cause problems in PC vision and image processing, such as detection of edge, video surveillance, stereo registration, object recognition, and image segmentation .To identify and remove the shadows from the image gives practical significance in image processing. Shadow forms when direct light cannot reach properly. It is classified into two categories: self shadow which is an area of an object that is not illuminated by direct light and another one is cast shadow. Cast shadow is a dark area projected by an object on the background. It is further classified into two categories umbra and penumbra which is shown in Figure 1.

Umbra formation occurs when direct light is completely blocked similarly penumbra formation occurs when direct light is partially blocked which is shown in Figure 2. Shadow free image is required in many situations. In the current scenario, Shadow detection and removal from the image is a challenging task. The popular methodology of shadow detection and removal are concentrated on the property of shadow pixels, such as regions of shadow having low intensity, high saturation, and hue. The area of shadow is

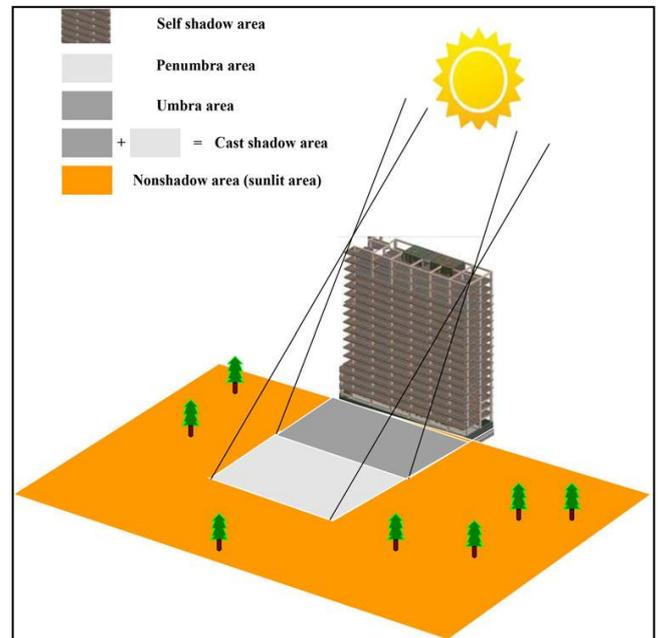


Figure 1. Shadow Formation

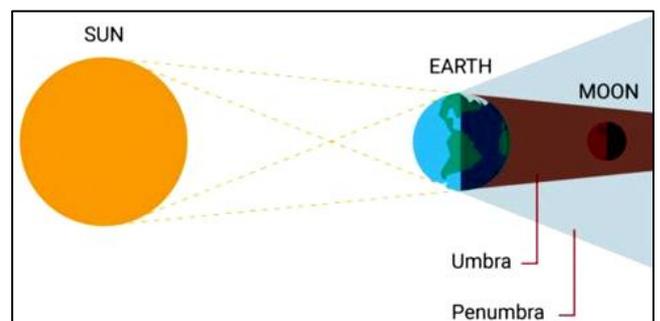


Figure 2. Umbra and Penumbra Formation

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Determined by thresholding method with a distribution of image histogram but thresholds detection results are more accurate when we use a near-infrared band for the image.



The published works in this area reflect the large impact. To identify the shadow pixels accurately there is the need of effective methods which should take care of shadows pixels and corresponding boundaries. To get back the data from the shadow area there are three main techniques of image enhancement like linear correlation, histogram matching, and gamma correlation is used. Over the past decades, Various color-based [1], edge-based [2], change in texture-based [3], and other methodology [4-7] for shadow detection and removal algorithms have successfully brought the desired objectives. In 2014, Song et al. [8] discussed example based learning methods for shadow detection and removal which models the relation based on Markov random field. They have also discussed the pair-wise regions. In 2015, Besheer et al. [9] improved invariant color model C1C2C3 with the help of near infrared information. They modify the C3 index into C3\* index for detection of shadow pixels. They have used a bimodal histogram method for thresholding to segment the image into non-shadow and shadow. In 2016, Su Nan et al [10] proposed a method of shadow detection and removal for remote sensing images to restore the object information. They have presented a soft shadow detection method by combining a bimodal histogram and image matting. They have also presented a spatial adaptive nonlocal sparse shadow removal technique which works at two stages, at first stage line correction methodology is used to improve shadow area and at second stage linear radiometric correction is used to control the brightness of shadow area. In 2017, Xu Mingliang et al, [11] discussed learning based shadow detection scheme in which, both shadow and invariant cues from texture and illumination are used to identify shadows. These properties are used to make a classifier with the help of a decision tree. They have also used a Gaussian model to remove the recognized shadows. In 2017, Mostafa et al [12] suggested a novel image index for shadow detection and removal, named shadow detector index to find a shadow in remote sensing images. They have considered RGB color band to identify the shadow pixel intensity then automatic threshold applied in the histogram. Besides, the shadow detector index shows stability in vegetation regions. Finally detected shadow is then compensated with the help of linear correlation correction method. In 2018, Zhu et al [13] discussed the effective approach for shadow detection based on reflectance in which an image is segmented and based on illumination, reflectance and texture characteristics segments pairs are evaluated as shadow and non-shadow regions. In 2018, Yan Li et al [14] suggested object-oriented shadow detection and removal method by regional matching and without manual intervention. They also suggested that the pixel based method, in which Gaussian mixture model is used to refine the soft shadow map. The shadow map is merged with image segmentation result to obtain shadow region. They have also used the total variation model to decrease noise and boundary effect. In 2019, Vicky Nair et al [15] discussed a system using machine learning approach for

shadow detection. They have used machine learning algorithm enhanced streaming random tree (ESRT) in which image is converted to HSV then relation file format is generated for shadow and non-shadow images. Finally, color chromaticity and morphological processing are applied to remove the shadow. In 2019 Das and shandilya [16] discussed the efficient artificial bee colony (ABC) with boundary value segmentation. In this method, the Otsu approach for thresholding, gradient segmentation, and ABC algorithm are used. First the data pre-processing has been applied for adjoin and adjacent matrix then association rules have been applied for adjoin and associated pixels and joint correlations have been formed. Finally, the ABC algorithm has been applied for the final object detection and tracking.

## II. METHODS

In this paper, the triangle method on histogram function is used to find the three threshold levels to identify pixels. These three levels are high, medium and low which is calculated by a line drawn between peak and largest nonzero value then the distance between histogram and line at the right angle is calculated, the distance which is maximum considered as the threshold. With the help of these thresholds mask of the image is created to find the true location of the boundaries and finally, IABC algorithm is used for final shadow detection as the classifier. The proposed method is divided into seven categories: 1)Image preprocessing 2) Thresholds selection 3) Masking 4) Boundaries evaluation 5) Curvature, edge response and gradient analysis 6) IABC algorithm 7) Filtering. First the image pre-processing has been performed to find the correlation matrix on the basis of that we evaluate edge map to store the depth of every surface. Based on correlation and edge map three thresholds are adaptively determined which is used to generate corresponding masks and boundaries. The curvature, edge response ,and gradient analysis are performed to find a complete mapping, smoothness of the curve and direction in which pixels change. Finally, an improved artificial bee algorithm (IABC) is used to detect the shadow and median filter is used for boundaries refinement and shadow removal. The algorithm 1 shows our approach. Figure 3 shows the proposed architecture.

### Algorithm 1: Improved Artificial bee colony with Multilevel thresholds and boundaries evaluation algorithm

Step 1: Input image

Step 2: Thresholds selection using triangle method that is a line drawn between peak and largest nonzero value then the distance between the histogram and line is calculated at 90°, the distance which is maximum considered as the threshold,

$$T(j) = \frac{C_1 N_2(j) + C_2 N_1(j)}{N_1(j) + N_2(j)} \quad (1)$$

where  $j=L, M, H$  corresponding to low, medium and high threshold.  $N_1$  represents pixel's number in  $P_1$  and  $N_2$  represents pixel's number in  $P_2$ .  $P_1$  is the false positive pixels and  $P_2$  is the true positive pixels.  $C_1$  and  $C_2$  is the modes of  $P_1$  and  $P_2$ .

Step 3: Based on three values of thresholds mask of the image is calculated as:

$$Mask_j = \begin{cases} 1, & \text{If } \Delta T(u, v) > T_T(j) \cup \Delta Y(u, v) > T_Y(j) \\ & \cup \Delta C(u, v) > T_C(j) \\ 0, & \text{Otherwise} \end{cases} \quad (2)$$

Where  $j=L, M, H$ . '1' means the foreground and "0" means the background. The masks of the input image corresponding to three levels of thresholds shown in Figure 4.

Step 4: Evaluation of boundaries value based on masks which are shown in Figure 5.

Step 5: The population based on the pixels have been evaluated. For every solution  $y_i$  ( $i = 1, 2, 3, \dots, m$ ) is a D-dimensional vector. where  $m$  represents the size of the population.

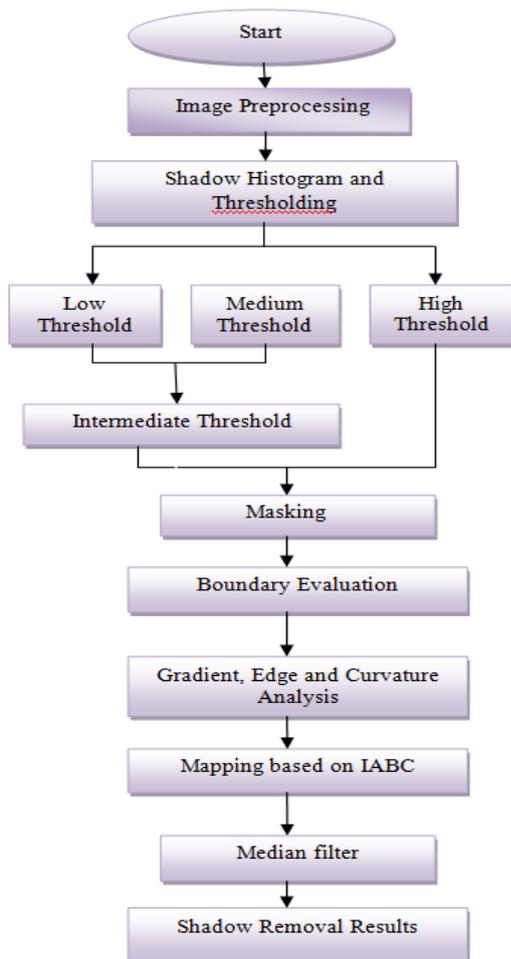


Figure 3: Proposed architecture of our approach.

Step 6: Fitness gain can be calculated by the scouts bee that is pixels in our case based on memory and neighborhoods pixels using a modified search equation.

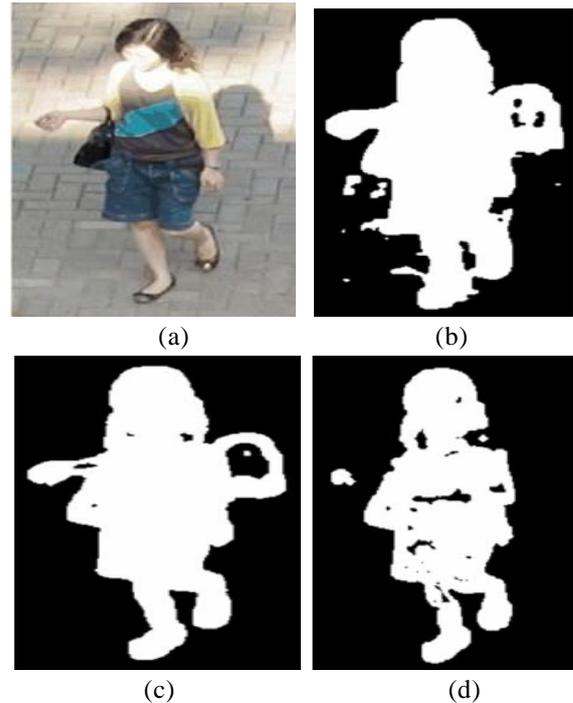


Figure 4. (a) Input image (b) Low Mask (c) Medium Mask (d) High Mask

$$Z_{ij}^{t+1} = x_{ij}^t + Y_j^{t+1} \quad (3)$$

Where  $Y_j^{t+1}$  is calculated by

$$Y_j^{t+1} = \alpha \times (v_j^t - x_{ij}^t) + \beta \times (u_j^t - x_{ij}^t) \quad (4)$$

In which  $v_j$  represents the  $j^{\text{th}}$  value of vector found by Population and  $u_j$  is the information of individuals in the population.

Where,

$$u_j^t = \sum_{i=1}^N (w_i^t \times x_{ij}^t) \quad (5)$$

$$w_i^t = F_i^t / \sum_{k=1}^N F_k^t \quad (6)$$

$$\alpha = r_1 + \frac{1}{2\pi} \sin(2\pi r_1) \quad (7)$$

And

$$\beta = r_2 + \frac{1}{2\pi} \sin(2\pi r_2) \quad (8)$$

$r_1$  and  $r_2$  are two real numbers within  $[0,1]$ .

Step 7: Find the probability by onlookers bee ( $B_j$ )

$$B_j = \frac{FV_j}{\sum_{n=1}^m FV_n} \quad (9)$$

where  $FV_j$  represents the fitness gain of the  $i^{\text{th}}$  solution.

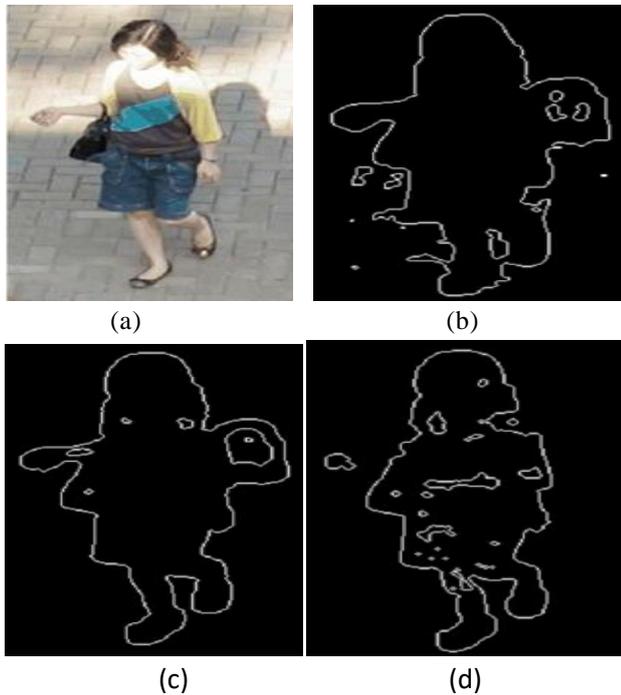


Figure 5. (a) Input image (b) Boundaries Low (c) Boundaries Medium (d) Boundaries High.

Step 8: Minimize the problems

Let the fitness gain as  $Fv$  and  $\sigma_i$  is objective function then two possibilities occur:

Case 1: If  $\sigma_i \geq 0$

$$Fv_i = \frac{1}{1+\sigma_i} \quad (10)$$

Case 2: Otherwise

$$Fv_i = 1 + |\sigma_i| \quad (11)$$

Step 9: Repeat the search process that is step 6 until the condition is satisfied.

Step 10: Finally Median filter is used to track the objects for shadow removal.

### III. RESULTS AND DISCUSSION

For experiment image of IKONOS is considered. The parameters considered to evaluate the shadow detection and removal performances are precision ratio  $P$  that measure the accuracy in case of true shadow. Recall ratio  $R$  reflects successfully detected shadow pixels. F-score 'F' consolidates both the ratio and keeps a balance between these two metrics.

$$\text{Precision (P)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (12)$$

$$\text{Recall (R)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (13)$$

$$\text{F-score (F)} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (14)$$

Overall Accuracy (OA) =

$$\frac{\text{True positive} + \text{True negative}}{\text{True positive} + \text{True negative} + \text{False positive} + \text{False negative}} \quad (15)$$

Figure 6. Shows the shadow removal results using IABC, Figure 7. Shows the precision values Comparison Figure 8. Represents the Recall values comparison Figure 9. Shows the F-score compared with other existing methods. Figure 10. Shows Overall accuracy comparison. The results clearly show that our approach has shown significant improvement in case of Precision, Recall, F-score and overall accuracy comparison.

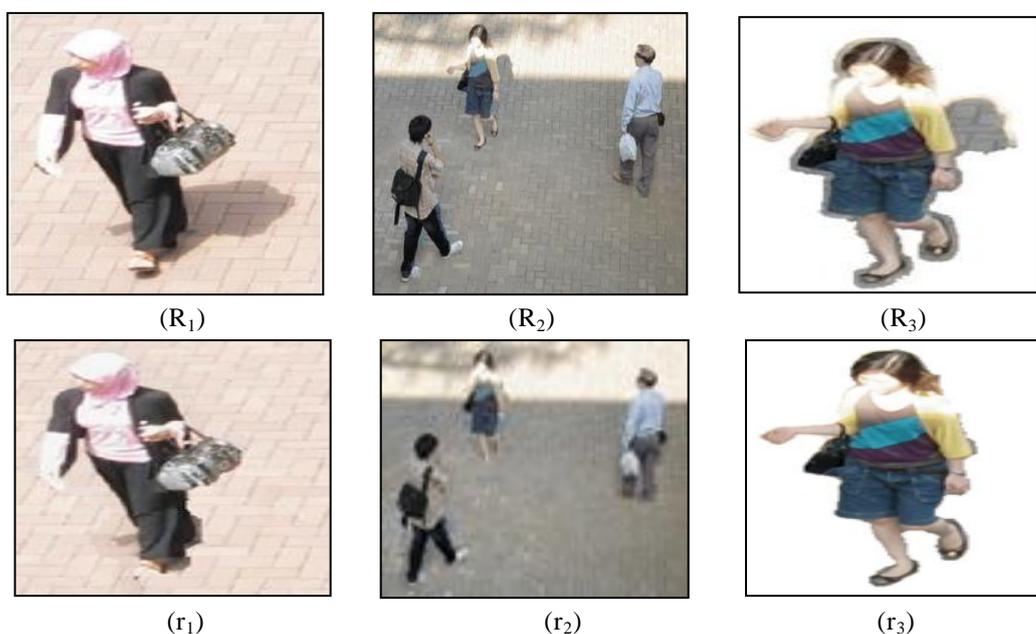


Figure. 6  $R_1$ ,  $R_2$ ,  $R_3$  Input images and  $r_1$ ,  $r_2$ ,  $r_3$  corresponding shadow removal results.

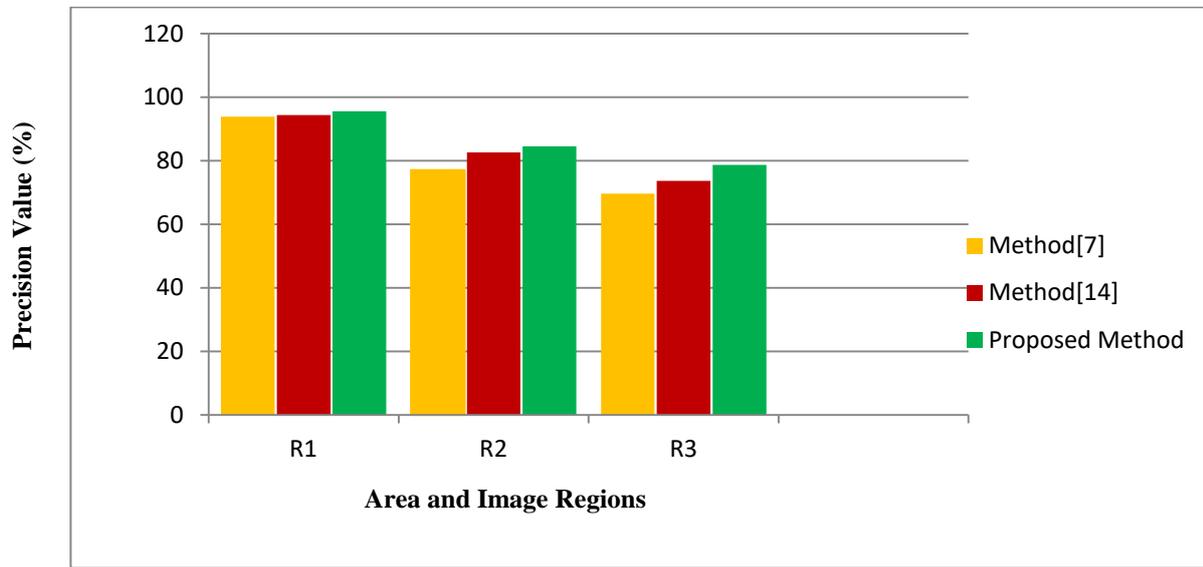


Figure.7. Precision values in different illumination conditions

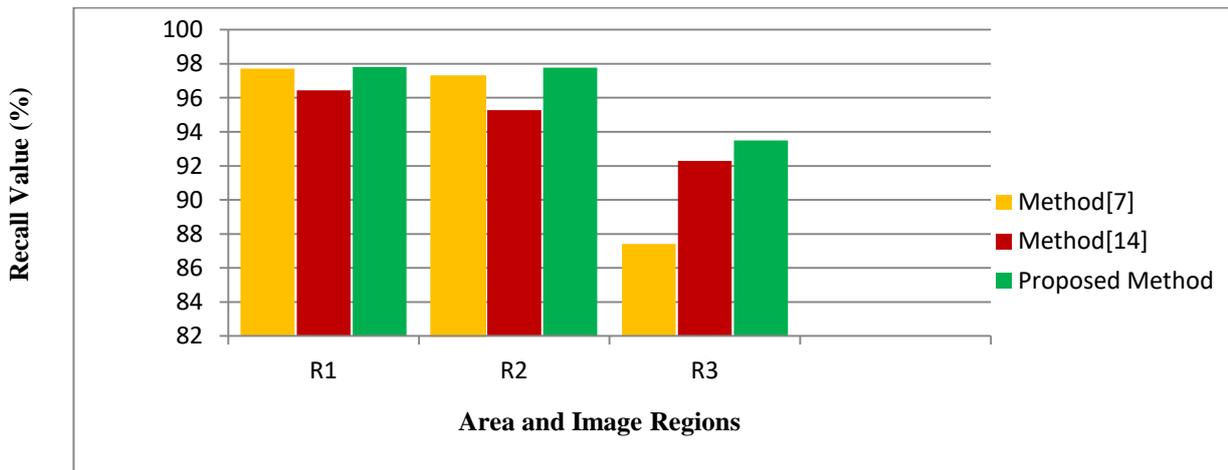


Figure.8. Recall values in different illumination conditions

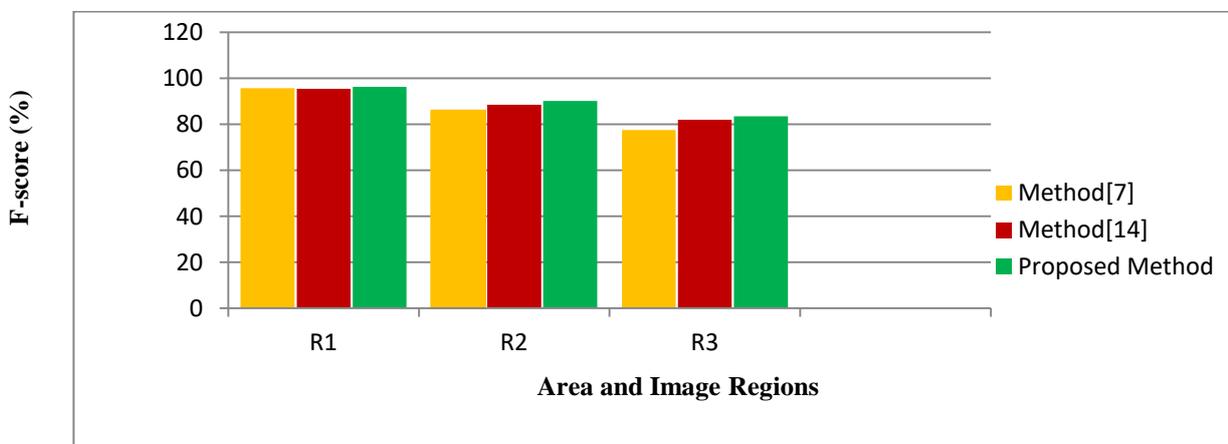


Figure.9. F-score values in different illumination conditions

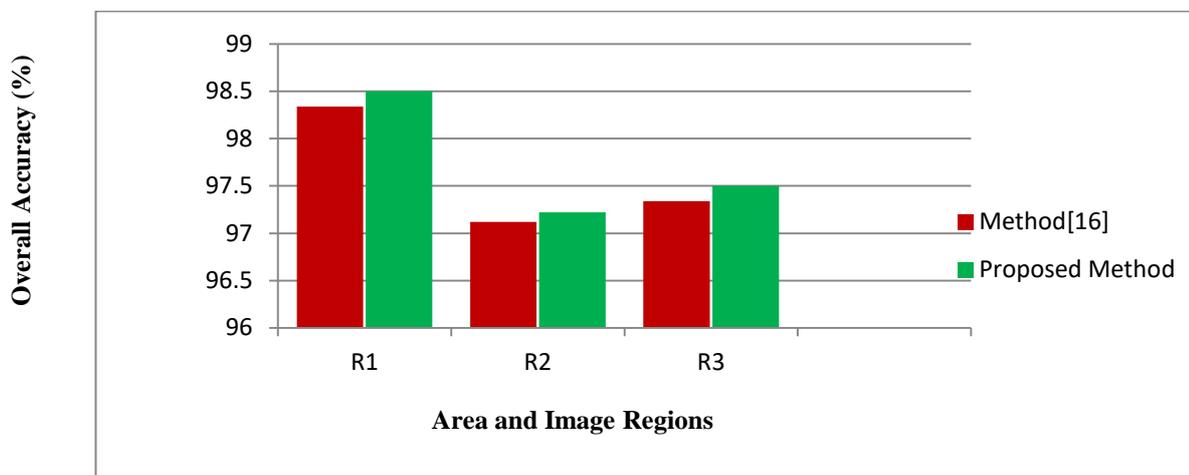


Figure.10. Overall accuracy comparison

#### IV. CONCLUSION

In this paper, we propose an improved artificial bee colony method IABC using three-level of thresholds and boundary evaluation to enhance its performance. We first introduce intelligent learning methods to increase the convergence rate. The concept of masking is used to improve the local boundary. The gradient, curvature evaluation, and edge response help to enhance accuracy. IABC is used to optimize the search process and to find the segmented and associated pixels for shadow detection. The recall values, precision values, F-score and Overall accuracy compare well with the existing methods. The result shows that the proposed method better than the previous one and other existing shadow detection and removal methods.

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