

RESEARCH ARTICLE

A Framework in Shadow Detection and Compensation of Images

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Received- 1 April 2016, Revised- 11 June 2016, Accepted- 29 August 2016, Published- 19 September 2016

ABSTRACT

Shadow detection and removal is a crucial and unavoidable task in computer vision algorithms. In this paper detection and reconstruction processes are employed separately on an image. In the detection process, the shadow and non-shadow parts of an image are detected separately using thresholding, histogram equalization and shadow masking. The reconstruction process can be split into two steps. The first step is the calculation of mean and standard deviation for the shadow and non-shadow parts and the second step is finding the difference between the shadow and non-shadow parts and applying these differences to the shadow part. The result is a quality image with non-shadow region.

Keywords: Thresholding, Histogram equalization, Compensation process, Shadow detection, Shadow masking.

1. INTRODUCTION

A shadow can be defined as an unwanted information that affects the quality of an image. The detection and removal of shadow in images is the main concept of this paper. The existence of shadows in an image is a major challenge when the images are used in real-time applications such as traffic surveillance where the image pixel quality is reduced and limits the system performance. The detection and removal of shadow in the image is the only way to solve this problem. Over the past years, a large number of significant research have been done on detecting and compensating shadows.

[1] presented a tricolour attenuation model to identify shadows in a single image. Shadow detection was performed by generation of an invariant image and segmentation was carried out. However the dark areas were not classified as shadows. [2] presented an entropy minimization method for the removal of shadow in an image. Here pixel value of the shadow image and non-shadow image was derived using entropy calculation method. The quadratic entropy was evaluated using the efficient Fast Gauss Transform

(FGT). This method was found to be quite reliable. However the resultant output was unsatisfactory due to the presence of shadow edges in the output image.

[3] used separate methods for both detection and removal. The hypothesis test was used for shadow detection method and energy function was used for the removal process. The lightening required in the shadow region was assumed to be a constant. But there were severe changes in the shadow-free output image when compared to the original image.

[4] proposed the region growing based shadow detection and removal method. Based on the illumination and graph, the segmented regions in an image were categorized. Then graph for shadow and non-shadow parts were labelled and lighting was done on the shadow pixels. Finally mean and standard deviation were calculated to recover the shadow free image. This method only removed 50 % of the shadow portion and the region growing failed when the intensity of the pixel value varied widely in the shadow part. In [5] multi-threshold image segmentation was done for the elimination of shadow in an image. It failed to restore the original background patterns. [6]

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Double blind peer review under responsibility of DJ Publications

<http://dx.doi.org/10.18831/djece.org/2016031001>

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introduced the IOOPL (Inner Outer Outline Profile Lines) method for shadow detection and removal. Here segmentation was done by using watershed algorithm and thresholding by Otsu's method. The detected boundary is applied to the IOOPL. Next, the inner and outer loop of the shadow is compared and the shadow is removed. But, colour variations occurred in the shadow free output image which affected the image quality as well as the reconstruction. [7] explained the adaption method for shadow detection and removal. The drawback was that masking was not able to accurately detect the edges and shadow areas. [8] highlighted the K means clustering method. Here cluster number was decided on the basis of data points. After clustering, mask is compared and the shadow area is detected. Then pixel values of the masked image and original image are evaluated and the difference in pixel variation is found. Finally the shadow portion is refilled by this difference. Presence of some noise in the resultant image reduced the method quality. [9] described a three step shadow removal process. In the first step one dimensional shadow free image was established. The second step was the creation of two dimensional colour representations. In the final step three dimensional shadow free colour image was produced. This method only removed the cast shadow of an object image. [10] presented the local Maximally Stable External Region (MSER) detector to identify the shadow region on high resolution images. But it has limited the shadow eliminating performance on high resolution remote sensing images. [11] explains about the Normalized Saturation-value Difference Index (NSVDI) in Hue-Saturation Value (HSV) colour space for identifying the shadow in an image. It was used along with histogram matching in order to retrieve the information below shadows. However this method has no particular strategy for dealing with the borders between shadow and non-shadow regions. [12] used the morphological filtering and example-based learning for shadow detection and reconstruction. The limitation was that it needed post-processing and result of this method could have blurred areas, holes and noise. [13] explained about the shadow removal based on Phong illuminating model and used thresholding on the difference of hue, blue and green-blue components in order to identify the shadow areas. It was further

compensated separately by Retinex technique. In [14] shadow detection was performed using luminance and colour information. Cast shadow and self-shadow were also classified as shadows by this method. These methods have certain restrictions and the results are not produced efficiently. [15, 16, 17] The shadow detection and compensation process were done by using Dual-Pass Otsu Method. The pixel value is separated in to high and low level intensities. Threshold is set to distinguish between self-shadow and cast shadow. The pixel of cast shadow is then replaced by pixel of the shadow background. This method is computationally inexpensive, but has low performance profile.

In the proposed method, efforts have been taken to minimize all the above mentioned problems and to provide a new accurate and efficient frame work for shadow detection and compensation.

2. PROPOSED METHOD

The method can be divided into two parts viz., shadow detection and shadow compensation.

2.1. Shadow detection

The shadow region has to be detected separately before applying the reconstruction process. The flow chart for shadow detection is indicated in figure 1.

The input image is RGB in nature. Initially the input RGB image is converted in to grey scale image using grey scale conversion algorithm for easier processing. The grey scale images are chosen for the reason that it requires less information for each pixel, when compared to colour images.

The conversion of a colour image to grayscale image is not unique. Diverse weighting of the colour channels effectively describe about the effect of shooting black and white film by different coloured photographic filters on the cameras. The RGB components all have equal intensity in RGB space but the gray colour needs to specify only a single intensity for each pixel. Hence this gray colour opposes those three RGB intensities which are needed to specify every pixel in a full colour image.

The grey scale conversion algorithm is applied to the input original image which consists of the shadow. This algorithm first calculates the length and width of the input

image and finds out the pixel value in integer format at (a, b) image position. Here 'a' and 'b' denotes the distance from the origin in the horizontal axis and vertical axis respectively. Then this integer value is converted in to a hexadecimal value and the pixel value of RGB is found out separately. Then the gray value of that pixel is calculated by using the equation (2.1)

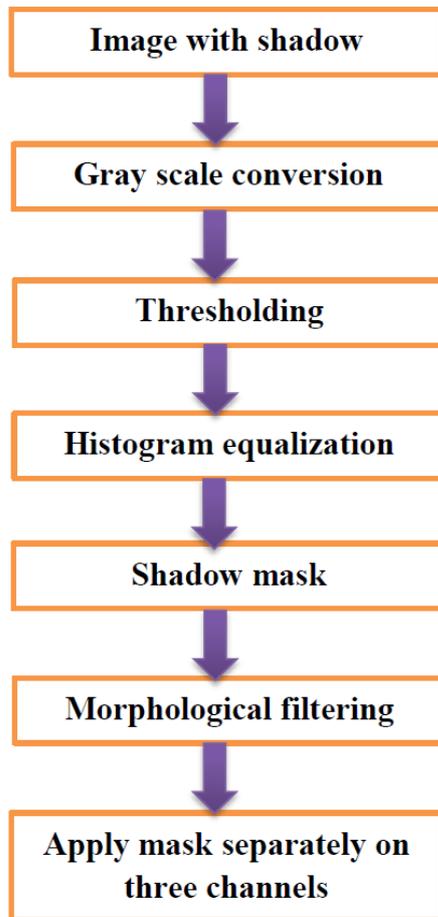


Figure 1. Flow chart for shadow detection

$$GRAY = \frac{(R+G+B)}{3} \quad (2.1)$$

This calculated gray value is applied to each pixel value of RGB(R=GRAY, G=GRAY, B=GRAY) and the pixel value is reset. Finally the gray scale image is generated.

2.1.1. Thresholding

Thresholding is the method of segmentation on the basis of the diverse colour or intensities in the background and foreground portion of an image. [16, 17] The input of the thresholding function is a gray scale image

which is derived from the above step. The output is a binary image representing segmentation. Black colour pixels indicate the background and white colour pixels represent the foreground or vice versa. In the implementation, the intensity threshold is compared with each pixel of an image. If the pixel intensity is higher than the threshold, the pixel is set to white in the output or else if it less than threshold, the pixel is set to black in the output. In this paper Otsu's thresholding is implemented in order to obtain a threshold to differentiate and store the pixel between the shadow and non-shadow regions. This Otsu thresholding algorithm is also called as global thresholding. The threshold value is calculated by using total mean and variance. Using this threshold value, each pixel of an image is set to background (0) or foreground (1). Thus, the image could change only once. If $g(x, y)$ is a threshold version of $f(x, y)$ at a certain Otsu threshold T , then as shown in equation (2.2)

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) \geq T \\ 0 & \text{otherwise} \end{cases} \quad (2.2)$$

The pixel value of images are spilt into two classes (C_1 and C_2) using gray levels (1, ..., t) of C_1 and (t+1, ..., L) of C_2 .

The probability distribution for the two classes [C_1 and C_2] is given by equation (2.3) and (2.4).

$$C_1 = p_1/w_1(t), \dots, p_t/w_1(t) \quad (2.3)$$

$$C_2 = p_{t+1}/w_2(t), \dots, p_L/w_2(t) \quad (2.4)$$

where $w_1(t) = \sum_{i=1}^t p_i$ and $w_2(t) = \sum_{i=t+1}^L p_i$

The mean for the two classes of the threshold image is given in equations (2.5) and (2.6)

$$\mu_1 = \sum_{i=1}^t p_i / w_1(t) \quad (2.5)$$

$$\mu_2 = \sum_{i=t+1}^L p_i / w_2(t) \quad (2.6)$$

The variance for the two classes of the threshold image is given in equation (2.7)

$$\sigma_B^2 = w_1(\mu_1 - \mu_T)^2 + w_2(\mu_2 - \mu_T)^2 \quad (2.7)$$

Optimal threshold of an image using Otsu's method is obtained by equation (2.8)

$$t^* = \text{Arg}_{t < L} \text{Max}\{\sigma_B^2(t)\} \quad (2.8)$$

2.1.2. Histogram equalization

Histogram equalization is a method for adjusting the intensities of an image in order to improve the contrast. It quantifies the number of pixels for each considered intensity value. Histogram provides the frequency levels of grayscale in an image. The histogram graph of an original input image is shown in the figure 2. The equalization indicates plotting the given histogram image to a wide range or uniform distribution of intensity values. Hence the intensity of the pixel values is spread into a wide range. To obtain equalization effect for the image, the remapping of histogram could be carried out. The remapping function is given as in equation (2.9)

$$H'(i) = \sum_{0 \leq j < i} H(j) \quad (2.9)$$

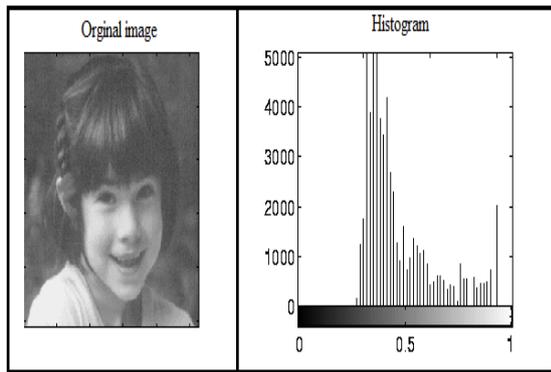


Figure 2. Histogram of an original image

where $H'(i)$ is the cumulative distribution and $H(j)$ is the histogram. Using this remapping function $H'(i)$ is normalized and the maximum value is 255.

The intensity pixel values of the equalized image are obtained as shown in equation (2.10)

$$\text{equalized}(x, y) = H'(\text{src}(x, y)) \quad (2.10)$$

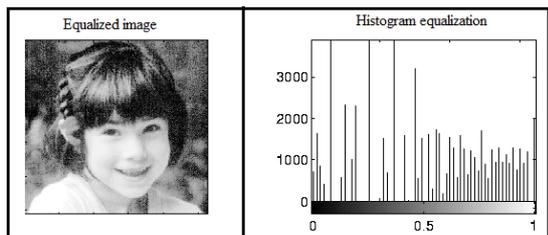


Figure 3. Histogram equalization

Figure 3 shows the histogram equalization of an image from the original image. Hence, from this step, the grey

threshold image contrast is enhanced and the histogram equalized intensity pixel value graph is derived.

2.1.3. Shadow masking

The next step in the shadow detection process is the shadow mask creation. The size of the shadow mask is same as that of the input image. In order to apply the mask, the threshold value and pixel value of the input image are compared. An initial shadow mask region is generated by the thresholding method. The shadow edge mask is estimated by comparing the raw input and invariant images. The Gaussian smooth filter is applied to both the original image and the invariant images. This method reduces the high frequency texture of the threshold image. Thus the smoothed image is obtained. Then edge detection is performed on both of the smoothed images.

2.1.4. Morphological filtering

Morphological filtering is a collection of non-linear operations related to the morphology of image features. It has a structuring element that defines the neighbourhood around the image pixel. Binary images produced by thresholding may contain some imperfections such as noise and texture. The main goal of morphological image processing is to remove such imperfections by accounting for the structure and form of the image. Thus the noise and wrong texture in the shadow mask are removed.

The next process of masking is performed by the morphological filtered mask. It finds the border pixels in a shadow region. Therefore the morphological filtered mask is then applied separately on three channels of the shadow image and is finally combined. As a result the shadow image is separately taken out from the original image.

2.2. Shadow compensation

After detection, the next process is to remove the shadow from the detected image. The compensation of shadow implies the removal of shadow in such an image. The flow chart for shadow compensation is shown in figure 4. This process can be split in to two steps. Initially shadow detected image is taken. The first step is calculating the mean of the shadow region and non-shadow region. In the mean calculation, first the length (l) and width

(w) of the image is calculated. Thus the obtained the pixel value is in an integer format at (x, y) where x is the horizontal axis and y is the vertical axis. The integer value of the pixel is converted into hexadecimal value and the pixel value of non-shadow and detected shadow image is found out. Next, the total for red colour, green colour and blue colour is set to null value. The hexadecimal value of red colour is added one by one in order to find the total mean value of red colour pixel. The mean value of red and blue colour is also found using the same procedure. Hence the mean value of red, blue and green colour of shadow region image are calculated using the given equation in (2.11)

$$\begin{aligned} R_m &= R_m + R \\ G_m &= G_m + G \\ B_m &= B_m + B \end{aligned} \quad (2.11)$$

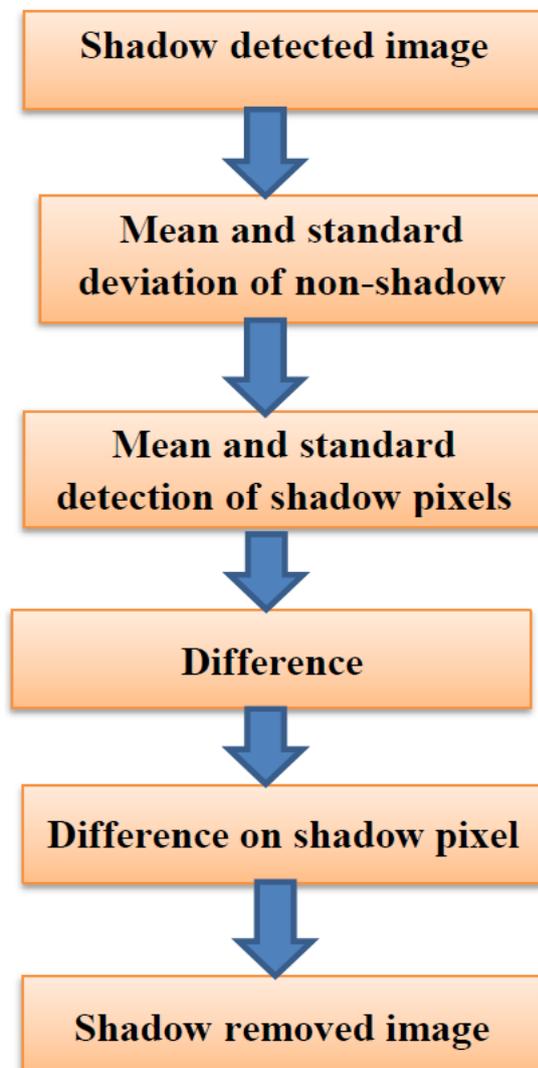


Figure 4. Flow chart for shadow removal

The same procedure is followed for calculating the mean value of non-shadow region of an image. Then the standard deviation for both the shadow and non-shadow regions of the image is calculated. The equation for the calculation of standard deviation is shown below in equation (2.12).

$$\begin{aligned} \mu_R &= \frac{R_m}{(L * W)} \\ \mu_G &= \frac{G_m}{(L * W)} \\ \mu_B &= \frac{B_m}{(L * W)} \end{aligned} \quad (2.12)$$

After calculating, the mean colour value and standard deviation for the shadow and non-shadow parts, the mean difference between the shadow and non-shadow region of the image is found out. The calculation of mean difference between shadow and non-shadow region is done by using equation (2.13).

$$D = |\mu_1 - \mu_2| \quad (2.13)$$

Then, this mean difference is applied on R (red), (G) Green, B (Blue) elements of the shadow part of an image. using normalization method with the help of standard deviation. Finally the output generated which is the shadow free image.

3. EXPERIMENTAL RESULTS

The shadow detection and compensation are implemented separately using MATLAB R2010. The whole process is tested using the real images. The shadow detection method performance is described as follows. The output of the each step of the shadow detection process is given below.



Figure 5. Input image



Figure 6. Greyscale image



Figure 7. Otsu threshold output

When compared to the existing method, the proposed method evaluates the pixel value level of shadow detection result with manually chosen correct threshold according to the image grey scale histogram image. The segmentation result shows that the problem of shadow being segmented as a whole object can be restricted. The histogram equalization adjusts the intensity pixel value and improves the image contrast. The recovery of shadow using Otsu's threshold and masking is done on the shadow image. Figure 5, figure 6 and figure 7 shows the input, greyscale and thresholded image respectively. The morphological filters remove the imperfection without changing the structure and form of the image. Finally the shadow portion and dark

object is separated and detected. The resultant output is shown in figure 8.

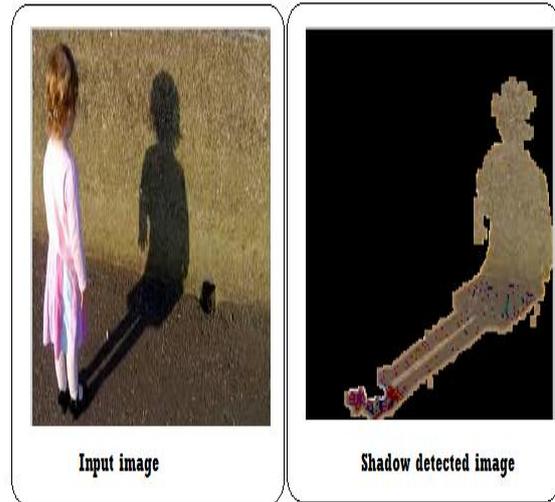


Figure 8. Shadow detected output

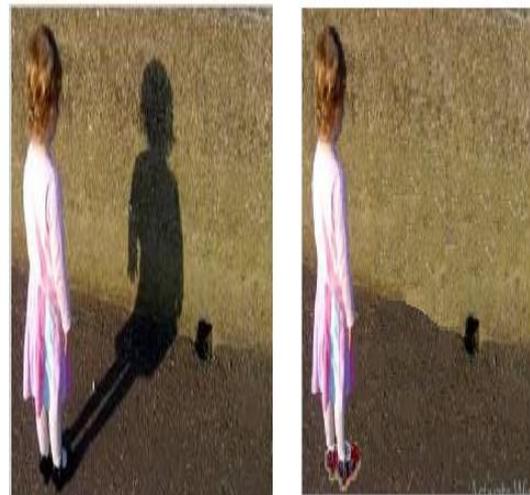


Figure 9. Output image with no shadow

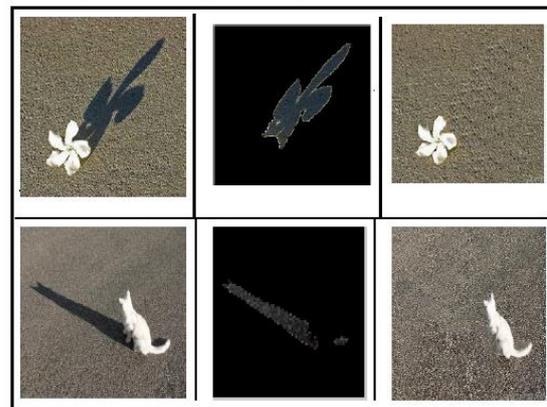


Figure 10. Various test images using proposed method

The shadow detected output is separately taken and is given as input to the

shadow removal block. The result shows the image with no shadow region and also compensates the dark object. The output result also matches the input image in terms of quality. The experimental output of the shadow compensation step is shown in figure 9. The output of various test images using this proposed method is given in figure 10.

Table 1 and figure A1 shows the comparison between some existing methods reported in the literature and our proposed method. It was found that the overall accuracy of the proposed method is more than 90% when compared to the existing methods. The accuracy level of the existing and proposed methods is compared in the graph (figure A1).

Table 1. Comparison of shadow detection and removal accuracy

Various Approaches	Accuracy of shadow detection	Accuracy of shadow removal
Dual-Pass Otsu Method [15]	70.6%	65.2%
K means clustering method[8]	89.6%	88.5%
IOOPL method [6]	84.8%	81.8%
Proposed method	95%	92.3%

Table 2. Comparison of average computation time

Various Approaches	Computation time for shadow detection	Computation time of shadow removal
Dual-Pass Otsu Method [15]	0.0980	0.9637
K means clustering method[8]	0.0670	0.6404
IOOPL method [6]	0.0770	0.7203
Proposed method	0.0440	0.4045

The average computation time for shadow detection and compensation process is found to be 0.0440 and 0.4045 respectively. It is far better than the existing methods. The

computation value of the proposed method and some of the related methods available in the literature is shown in table 2. The graphical representation of this comparison values in seconds is indicated in figure A2. Hence the result shows that the overall performance of the proposed method is very efficient.

4. CONCLUSION

This paper describes about a framework of shadow detection and removal using two separate methods. In the shadow detection process, the shadow part is identified by using thresholding, histogram equalization and shadow masking. Then the shadow region is taken for the removal process and a set of predefined procedures is performed on this image to refill the shadow. The resultant outputs for each method are derived by using MATLAB software. The results indicated better accuracy and performance. However, further research is required in the future in order to produce cent percentage efficiency.

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APPENDIX A

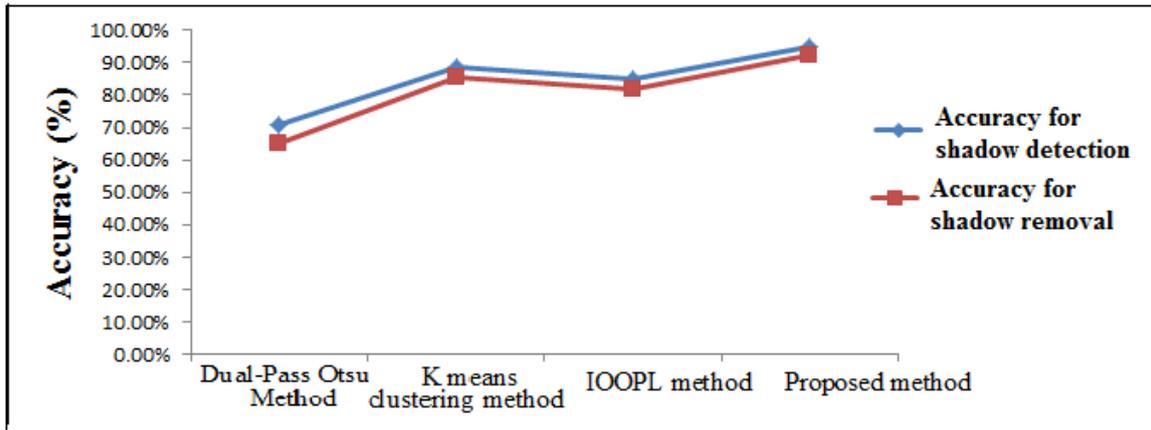


Figure A1.Schematic representation of accuracy rate

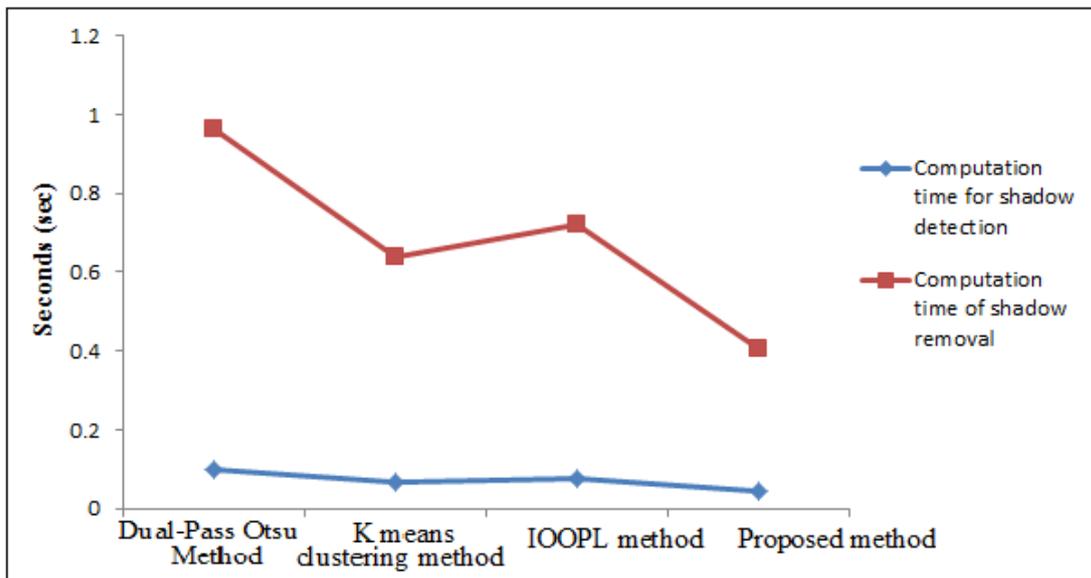


Figure A2.Graphical representation of computation time (sec)