Illumination Normalization for Image Restoration Using Modified Retinex Algorithm

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Abstract— **This paper presents a novel method of illumination normalization based image restoration. A modified retinex algorithm is proposed to remove the shadow and restore the image. First, image is split into illumination (L) and reflectance (R) components. The Reflectance component is subjected to threshold filtering while the illumination component is subjected to modified retinex algorithm and the resulting reflectance component is combined effectively with the output of threshold filter for obtaining the shadow-free image. Illumination normalization is performed on both small-scale as well as large-scale features. Using this approach, face images with cast shadows are normalized efficiently. The quality of the illumination normalized image is evaluated by means of JPEG quality score and PSNR values. We observed very good quality score for illumination normalized images in comparison with original images. The proposed method has a great potential in real-time face recognition systems, especially under harsh illumination conditions.**

Keywords-- retinex algorithm, illumination normalization, small scale features, large scale features, shadow removal.

I. INTRODUCTION

Shadows often introduce errors in the performance of computer vision algorithms such as object detection and tracking. This paper proposes a method to remove shadows from images based on modified retinex theory. Doing so can significantly improve and facilitate the performance of certain computer vision tasks, such as tracking, segmentation, and object detection, where shadow boundaries are often confused with those of different surfaces or objects. It is therefore of great importance to discover ways of properly detecting shadows and removing them while keeping other details of the original image intact. Lot of research is going on to detect shadows. Finlayson et al. [1] proposed the invariant image method, which requires the knowledge of the characteristics of capture device to color calibrate the camera. Levine and Bhattacharyya [2] proposed to manually train a support vector machine to segment an image into shadow and non-shadow regions. After validating the classifier, the shadowed regions are found. Weiss in [3] proposes to acquire a sequence of images in which the shadow edges move. The median of this sequence is calculated for each pixel and amounts to the maximum-likelihood estimation of the reflectance only image. Although his method results in very natural looking images, one of the shortcomings of this method is that it is not always practical to acquire a sequence of images where all the objects and surfaces do not move and just changing the illumination generates moving shadow edges.

Fredembach and Susstrunk [4] presented a simple and accurate shadow detection method that employs the inherent sensitivity of digital camera sensors to the near-infrared (NIR) part of the spectrum. Incorporating the features offered by the NIR band along with color information has recently drawn the attention of researchers in many imaging applications, such as illumination estimation [5], dark flash photography [6], video conferencing [7], object segmentation [8], and scene recognition [9]. Using the property of the NIR band, in which most of the colorants are transparent or have higher reflectance [10], the authors showed that combining the dark map of both visible and NIR images with ratios of the color channels (red, green and blue) to NIR identifies the pixels that are shadow candidates. Most existing methods for face recognition such as principal component analysis (PCA), independent component analysis (ICA), and linear discriminant analysis (LDA) are sensitive to illumination variations [12]. Hence face illumination normalization is a central problem in face recognition and face image processing as well.

Many well-known algorithms have been developed to tackle this problem. It was found that among the methods of extracting the illumination insensitive/invariant features, the retinex theory-based methods always perform better than the others [11]. However, the large-scale features of a face image, which may also contain useful information for recognition, are always discarded in these methods. Furthermore, without the large-scale features, it is certainly hard to generate a frontal-illuminated image with a good visual quality. Hence we have decided to consider both small and large-scale features. The problem of shadows in images captured by surveillance cameras is keenly addressed. Our modified retinex method was mainly designed to tackle this problem. Histogram equalization is done in order to improve the appearance of gray scale image. It is just a post-processing done for improving the visual quality of the processed image. Our algorithm does not require any complex data training or machine learning but still works well even in poor illumination conditions and gives a real-time response.

II.THE LARGE- AND SMALL-SCALE FEATURES NORMALIZATION

The large- and small-scale features (LSSF) normalization technique is a normalization technique first proposed in [11].

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The technique normalizes the input image by first computing the reflectance and luminance components of the image and then further processing both computed functions using a second round of normalization. The method implemented in this paper uses the SSR as the tool for illumination normalization in two steps as shown in figure1. We do not implement the non-point light technique which requires training data because this would limit the applicability of the technique to frontal images. The LSSF technique is implemented such that it has the prototype as shown in TABLE I.

Based on the Lambertian reflectance theory [15], a face image can be described by

$$I(x,y)= R(x,y).L(x,y) \quad (1)$$

where R is the reflectance component (albedo) and L is the illumination effect. R depends only on the surface material of an object, so it is the intrinsic representation of a face image. Many existing methods attempt to extract the reflectance component for face recognition. Unfortunately, estimating R from I is an ill-posed problem [14]. To solve this problem, Chen *et al.* proposed a more practical model [12]. In this model R_l is denoted as the albedo of large scale skin areas and background. Then, based on (1), the following decomposition is obtained:

$$I(x,y)= \frac{R(x,y)}{R_l(x,y)} R_l(x,y)L(x,y) = \rho(x,y)S(x,y) \quad (2)$$

TABLE I
PARAMETERS OF LSSF NORMALISATION TECHNIQUE

Inputs	*X*	a grey-scale image of arbitrary size
	normalize	a parameter controlling the post-processing procedure: 0 - no normalization 1 - perform basic normalization (truncation histograms ends and normalization to the 8-bit interval) by default
Outputs	*Y*	shadow- free gray scale image

In this case, the term $\rho = \frac{R(x,y)}{R_l(x,y)}$ contains only the small intrinsic features and S contains not only the extrinsic illumination and shadows cast by bigger objects, but also the large intrinsic facial structure. In this paper, We call ρ, the small-scale features and S the large-scale features. Analysis results from [11] suggest that both small and large-scale features are useful for object recognition in surveillance applications. Therefore, finding a way of normalizing these features properly is very important. Based on the decomposition in (2), illumination normalization could be performed on S, while the small intrinsic facial features ρ could almost remain unchanged. Even some necessary processing is required on ρ which is independent of that on S. To this end, we propose a novel method for illumination normalization, which normalizes separately the large-and small-features, as shown in Figure 1.

A. Modified Retinex algorithm

The single scale retinex (SSR) method was proposed by Jobson et al. in [13]. The function performs photometric normalization of the image X using the retinex technique. It takes either one, two or three arguments with the first being the image to be normalized, the second being the size of the Gaussian smoothing filter and the third being a parameter controlling whether post processing (i.e., truncation of the histogram ends) is performed or not (0 - no post processing, 1- truncation of the histogram ends and range adjustment to the 8 bit interval).If no parameter "h_{siz}" is specified or the parameter is specified in the form of empty brackets a default value of h_{siz}=15 is used. The function returns the photometricaly normalized form of the input image X in the output R. Since the technique is based on the retinex theory (image = reflectance*luminance), the function can optionally return the estimated luminance function in L as well. The input and output arguments of the modified retinex algorithm is shown in TABLE II.

TABLE II
PARAMETERS OF MODIFIED RETINEX ALGORITHM

Inputs	*X*	a grey-scale image of arbitrary size
	h_{siz}	a size parameter determining the size of the Gaussian filter (default: hsiz=15), hsiz is a scalar value.
	normalize	a parameter controlling the post-processing procedure: 0 - no normalization 1 - perform basic normalization (truncation histograms ends and normalization to the 8-bit interval) by default
Outputs	*R*	- a grey-scale image processed with the SSR algorithm (this normalized version of the input image is commonly referred to as the reflectance)
	L	- the luminance function estimated from the input grey-scale image X using the SSR technique

The algorithm for our modified retinex algorithm is as follows:

Step-1: The SSR function is applied to the input image which yields illumination (L) and Reflectance (R) components of the image in the log-domain. L corresponds to the large-scale features while R corresponds to the small-scale features.

Step-2: Compute antilog of the R and L components which results in R' and L' respectively.

Step-3: Small-scale features (R') are subjected to threshold filtering to obtain (R_l). Large-scale features are subjected to another SSR operation that results again in illumination component (L_s) and Reflectance (R_s) components. *Ls* contain the shadows that are eliminated.

Step-4: Compute the antilog of *Rs*.

Step-5: R_1 obtained in step-3 is combined with the output of step-4 to yield a shadow-free illumination normalized image.

Step-6: Histogram equalization is performed on the output of step-5

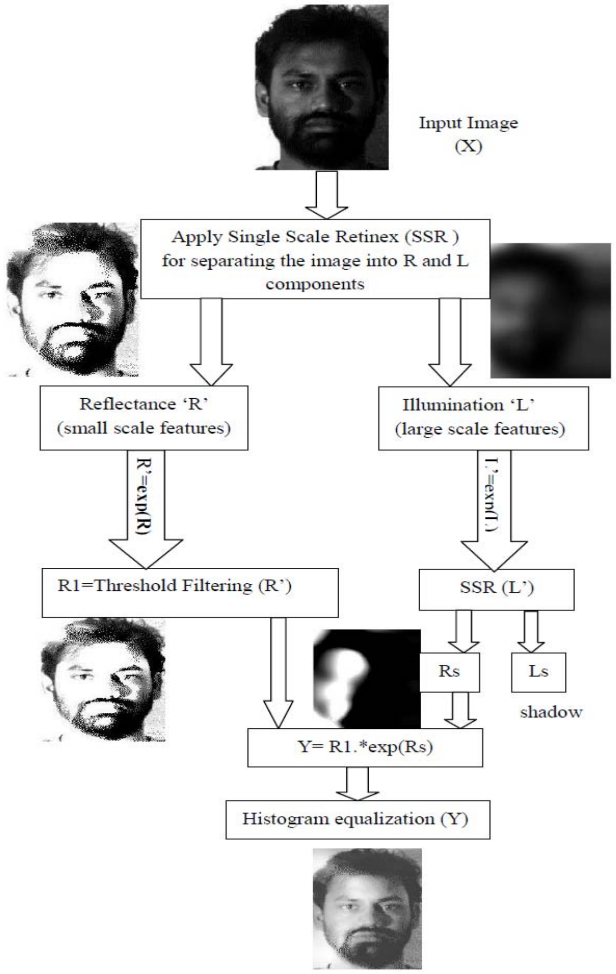


Figure 1: Flow chart of proposed system

Small scale features: lines, edges and small-scale objects
Large scale features: illumination and shadows

B. Threshold filtering

Threshold filtering is performed as suggested in [13]. Basically, the technique applies a local averaging filter to a local pixel neighborhood of size "mask size x mask size", but only if the center pixel value is larger than a threshold. This threshold is determined adaptively in such a way, that only the specified "percentage" of pixels has a larger value than the threshold. Effectively, this means that only the specified "percentage" of pixels is replaced through the averaging operation.

C. Histogram equalization

It is a method that usually increases the global contrast of images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. Hence areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. This serves as a post-processing step for our system.

D.JPEG Quality Score

JPEG is a block DCT-based lossy image coding technique. It is lossy because of the quantization operation applied to the DCT coefficients in each 8x8 coding block. Both blurring and blocking artifacts may be created during quantization. The blurring effect is mainly due to the loss of high frequency DCT coefficients, which smoothes the image signal within each block. Blocking effect occurs due to the discontinuity at block boundaries, which is generated because the quantization in JPEG is block-based and the blocks are quantized independently. One effective way to examine both the blurring and blocking effects is to transform the signal into the frequency domain. We denote the test image signal as x(m, n) for $m \in [1,M]$ and $n \in [1,N]$, and calculate a differencing signal along each horizontal line:

$$d_h(m,n) = x(m,n+1) - x(m,n), \quad n \in [1, N-1] \qquad (3)$$

We have used a computationally inexpensive and memory efficient feature extraction method. Features are calculated horizontally and vertically. The steps involved in jpeg quality score (QS) calculation is shown below:

(1) Blackness is estimated as the average differences across block boundaries.

$$B_h = \frac{1}{M(\lfloor N/8 \rfloor - 1} \sum_{i=1}^{M} \sum_{j=1}^{\lfloor N/8 \rfloor - 1} |d_h(i,8j)| \qquad (4)$$

(2) Activity of image signal is measured using two factors.

(a) Average absolute difference between in-block image samples:

$$A_h = \frac{1}{7}\left[\frac{8}{M(N-1)} \sum_{i=1}^{M} \sum_{j=1}^{N-1} |\, d_n(i,j)| - B_h\right] \quad (5)$$

(b) Zero crossing (ZC) rate: We define for $n \in [1,N-2]$,

$$Z_h(m,n) = \begin{cases} 1 \; if \; horizontal \; ZC \; at \; d_h(m,n) \\ 0 \; otherwise \end{cases}$$

Horizontal ZC rate can be estimated as

$$Z_h = \frac{1}{M(N-2)} \sum_{i=1}^{M} \sum_{j=1}^{N-2} Z_h(m,n) \qquad (6)$$

(3)Similarly calculate the vertical features B_v, A_v *and* Z_v. Finally the overall features are given by

$$B = \frac{B_h + B_v}{2}, A = \frac{A_h + A_v}{2}, Z = \frac{Z_h + Z_v}{2} \qquad (7)$$

(4)We combine the above features to form the quality assessment model for evaluating QS as follows:

$$S = \alpha + \beta B^{\gamma 1} A^{\gamma 2} Z^{\gamma 3} \qquad (8)$$

Where $\alpha, \beta, \gamma 1, \gamma 2, \gamma 3$ are the model parameters that must be estimated with subjective test data as in [16]. The parameters obtained with test images are $\alpha = -245.9, \beta = 261.9, \gamma 1 = -0.0240, \gamma 2 = 0.0160, \gamma 3 = 0.0064$ respectively.

III. RESULTS AND DISCUSSIONS

In order to prove the effectiveness and compatibility of our proposed algorithm we have tested our algorithm with a wide range of images like face image, Image of poorly illuminated room, Image captured from a street having shadow of buildings and partially visible face of a child hiding in a dark room. Histogram equalization can be used to further enhance the image. This is done to reduce the artifacts created during illumination normalization. It is seen in Figure 2 and 4 that the shadows that partially cover the face being removed by our algorithm. In Figure 3(a), some objects that are hanging on the chair and placed on table are invisible. The white circle in Figure 3(c) shows that the invisible details are restored as a result of illumination normalization.

All the images used here are in JPEG format. In order to prove that our algorithm has produced a good quality image compared to the input image, we have computed the QS as given in II (D). The parameter values for $\alpha, \beta, \gamma 1, \gamma 2, \gamma 3$ are also given in II (D). Input images are the images shown in Figure 2(a),3(a),4(a) and 5(a) and the corresponding output images are given in Figure 2(c),3(c),4(c) and 5(c) respectively. The QS of both input and output images are plotted in the bar chart shown in Figure 6(a). It is observed that the QS of shadow-free output images obtained using our algorithm are better than that of the input images. The PSNR values of output images obtained are plotted against different illumination conditions of input image in Figure 6(b). It is observed that the PSNR values are fair enough to judge that the illumination normalized shadow-free images have good quality.

Extended Yale B database consists of images obtained from 38 individuals and captured using 64 different lighting conditions from nine views. From this database we have selected some six images that have suffered poor lighting conditions for testing purpose. Experimental results obtained using those six images are shown in Figure 7. All those images were successfully restored by our proposed system. In order to calculate the quality of the illumination-normalized image, we have used the JPEQ QS. Results shown in Figure 8 reveal that even images from extremely poor lighting conditions were also successfully restored using our illumination- normalization approach. The QS of the illumination-normalized image in case: 5 of Figure 8 is less than that of the original image. But while seeing the corresponding illumination-normalized image in Figure 7(e), we can observe that most of the invisible information in the original image has been restored.

(a) (b) (c)

Figure 2:Testing on face image (a) face image with shadow (b) illumination normalised image (c) shadow-free face image (after histogram equalisation)

(a) (b) (c)

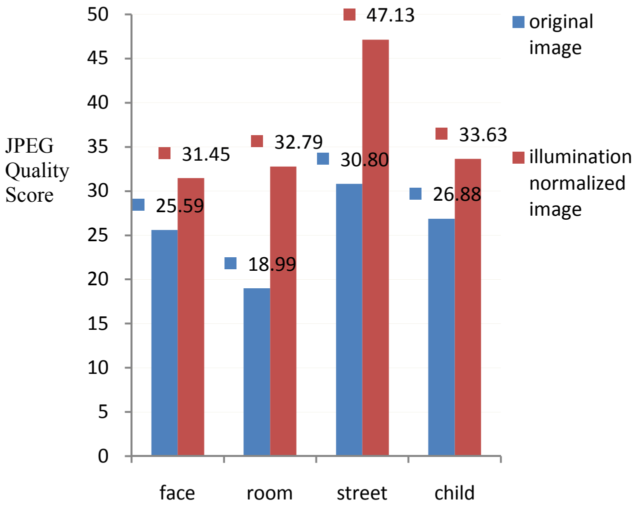
Figure 3: Testing on poorly illuminated room (a) room image (b) illumination normalized image (c) shadow-free image (after histogram equalization)

(a) (b) (c)

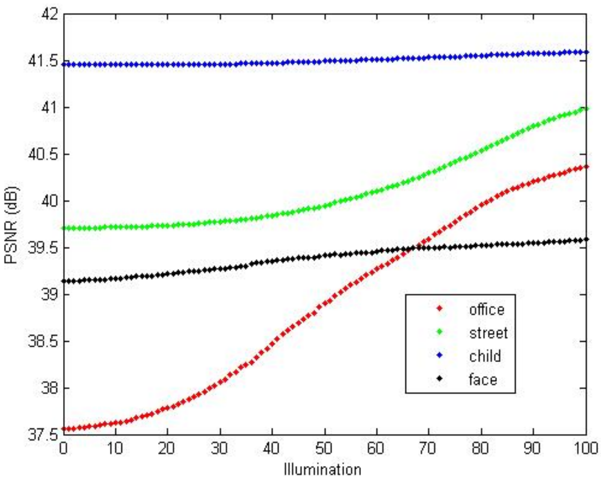
Figure 4: Testing an image captured from a street with shadow of buildings (a) street Image (b)illumination normalized image (c)image after histogram equalization.

(a) (b) (c)

Figure 5: Testing an Image of a child hiding in darkness (a) child image (b) Illumination normalized image (c) image after histogram equalization.



(a)



(b)

Figure 6: Quality assessment of normalized images (a) Using JPEQ quality score of input and output images (b) Using PSNR at different illumination conditions.

IV.CONCLUSION

In this paper modified retinex algorithm for shadow removal is proposed. Starting from the Lambertian reflectance theory and applying our modified retinex algorithm for normalizing both small and large scale features, makes this method compatible for face images and also images captured by surveillance cameras in a variety of scenarios. Removal of shadows serves as a pre-processing step before performing object segmentation and tracking in surveillance applications. It is demonstrated that both small and large-scale features are vital for face restoration and recognition. The quality of the obtained results is evaluated using JPEG QS and PSNR calculations. The QS of illumination-normalized images were found to be higher than that of input.

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Figure 7. Examples of illumination normalization of images from Extended Yale B database under poor illumination conditions: (a) original face image (b) small-scale features (c) large scale features (d) small-scale features subjected to threshold filtering (e) illumination-normalized images after histogram equalization.

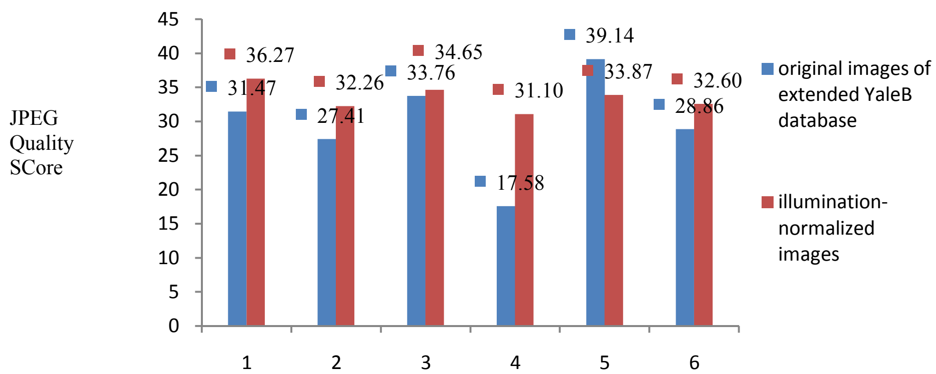

Figure 8: Quality assessment of illumination- normalized images of Extended Yale B database