Optik - International Journal for Light and Electron Optics 183 (2019) 483–495

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.com/locate/ijleo

Original research article

# Uneven illumination correction of digital images: A survey of the state-of-the-art

Nilanjan Dey

*Department of Information Technology, Techno India College of Technology, West Bengal, India*

ARTICLE INFO

*Keywords:*
Uneven illumination correction
Illumination models
Background correction techniques
Objective assessment techniques

ABSTRACT

The common image related artifacts during image acquisition are noise caused due to external interference and imbalance in illumination. Uneven illumination correction incorporates a penalty term that performs intensity distribution, and transfer between pre-defined uniformly illuminated and non-uniformly illuminated sub-regions of the input scale image. Many methods exist in the literature to address illumination correction. In this study, an overview of illumination models, estimation, unevenly illuminated image processing, non-uniform illumination correction, background correction techniques, and shadow correction are delivered. Various real-life applications, in the field of remote sensing imaging, automatic medical diagnosis of different diseases, underground imaging, and document imaging depend on image quality and illumination conditions. Some of the related work done by different researchers in solving illumination correction is discussed in a sequel. Assessment of correction quality is difficult because of non-availability of unilluminated images. Some of the objective assessment techniques are also discussed in this survey. This study aims at putting forward an all-inclusive discussion on the application of non-uniform image processing by means of various existing correction models in a wide application domain, and their frequently encountered challenges.

## 1. Introduction

Significant growth of low-cost digital imaging is noticed in recent times. Devices used in capturing images under uneven lighting, such as smartphones, digital cameras and likewise other personal digital assistants often result in images experiencing non-uniform illumination. The main reason behind unevenly illuminated images are (a) unstable lighting, (b) uneven distribution of light generated due to the presence of large objects, and (c) shadow of other objects makes it difficult to optically isolate the scene [1–3]. Under high illumination variations, in most of the cases, traditional adaptive threshold based segmentation techniques fail to detect small regions or objects and results in over-segmentation. Detection of foreground objects from a non-uniform image background using unsupervised segmentation technique is always vulnerable in the presence of various noise components, shadows (false detections) and reflections from light sources. For uneven background images, the main challenge is to solve the ill-posed inverse problem for correction of background signals without distorting the foreground.

Relatively complex images have an extensive range of varying signal-to-noise ratio. The chance of edge loss in the low-intensity region increases on application of edge detection operators and edge redundancy in the light surface [4].

Captured textures might differ even in conditions where an image of the same surface is taken under varying illumination directions. The extracted features from the same surface are called “illumination-sensitive” texture features. “Illumination-sensitive” texture features affect the performance of traditional classifiers [5]. To improve the overall performance, de-noising [6,7] and

*E-mail address:* neelanjandey@gmail.com.

https://doi.org/10.1016/j.ijleo.2019.02.118
Received 22 February 2019; Accepted 22 February 2019

illumination normalization are required. Illumination normalization is a technique to obtain normalized images from images of unconstrained illumination conditions [8]. An outline of uneven background correction techniques is discussed which needs to be deployed on digital images in various application areas under uneven lighting conditions. Prospective correction is *a priori* correction [9], which is used during image acquisition, whereas retrospective correction is *a posteriori* correction applied after the acquisition. A detailed discussion of the same is provided in Section 4.

This study aims at reporting various techniques of image processing and analyses (e.g.- segmentation [10–15], edge detection [16–21], etc.) and mechanism of texture feature extraction [22–25], which are required for image processing in unconstrained illumination conditions. This survey proposes to provide an accommodating review of existing literature in the domain of uneven image processing and thereby filtering out possible areas having potential for future research.

The schema of the paper is as follows: in Section 2, illumination model and estimation techniques are briefly introduced. Sections 3 and 4 report various uneven illumination image processing and uneven illumination normalization, background correction, and shadow removal techniques. Section 5 is dealing with applications of uneven illumination corrections, while Section 6 deals with objective assessment. Section 7 concludes the proposed ideas of the author and finally discusses the avenues where future research can be directed.

## 2. Illumination

The appearance of surfaces under various lighting conditions is needed to be simulated in order to produce realistic images.

### 2.1. Illumination model

Reflected light quantifies illumination incident at a point on a surface.

The lighting impacts are depicted with models that take into account the interaction between light sources and object surfaces. The lighting impacts determining factors include (I) parameters of the light source (electromagnetic spectrum, positions, and shape), (II) parameters of the surface (reflectance properties, position, a position of adjacent surfaces) and (III) parameters of the eye (camera) (sensor spectrum sensitivities, position). The illumination model computes the intensity of the reflected light on a surface at a specified point. Three basic models are proposed based on the standard lighting conditions in a scene. In [26] a detailed discussion of all these 3 different model types is clearly discussed.

#### 2.1.1. Ambient light (Model I)

Illumination of a particular object is due to the presence of ambient light that enters into a room and bounces several times throughout the room. The light's ambient color and the ambient material color contribute to ambient lighting.

The ambient term of a given light is mathematically represented as follows:

$$I_A = L_i L_A M_A \tag{1}$$

where $L_i$ is the illumination, $L_A$ is the light's ambient color and $M_A$ is the ambient material.

The color and intensity of the light are represented by *light's ambient color,* whereas the surface reflection of ambient light (as a whole) is represented by the *ambient material* color.

#### 2.1.2. Diffuse light (Model II)

The influence of *diffuse light* (generated from direct light hitting the surface) is dependent on the incident angle. This influence is directly proportional to the incident angle. The depending factors for *diffuse light* are namely: (I) light colors, (II) material colors, and (III) illuminance (IV) normal vector.

The representation of *the diffuse light*can be expressed as:

$$I_D = L_i \max(0, \widehat{L}_{Dir} \bullet \widehat{nor}) L_{Diff} M_{Diff} \tag{2}$$

where $L_i$ is the illuminance, $L_{Diff}$ is the light diffuse color, $M_{Diff}$ is the diffuse material, $\widehat{L}_{Dir}$ is the light director, and $\widehat{nor}$ is the surface normal vector.

#### 2.1.3. Specular light(Model III)

Specular light is observed on smooth, shinny objects as a white highlight reflection. Specular light depends on (I) light direction, (II) surface normal, and (III) viewer location.

*Specular light* is represented as follows:

$$I_s = \begin{cases} L_i \max(0, (\widehat{ref} \cdot \widehat{v}))^m L_s M_s, & if \widehat{L}_{Dir}.\ \widehat{nor} > 0 \\ 0, & otherwise \end{cases} \tag{3}$$

where $L_i$ is the luminance, $\widehat{ref}$ is the reflection vector, $L_s$ is the light specular color, $M_s$ is the specular material, and *m is the shininess coefficient.* The *Reflection Vector* is presented as:

$$\widehat{ref} = 2(\hat{L}_i \cdot \widehat{nor})\widehat{nor} - \hat{L}_i \tag{4}$$

A detailed discussion on the ambient light illumination model is presented in [27]. An illumination model for skin layer bounded by rough surfaces has been stated in [28]. In [29], a discussion of the illumination model inverted from the range and intensity maps was considered.

Parameter estimation for an illumination model using photometric stereo is addressed in [30]. Phong illumination model and infrared sensors are used to measure distances [31]. Illumination models are also used in various application areas like face recognition [32], face alignment [33], soft X-ray transients [34], smart indoor solid-state lighting [35], optical satellite data of rugged terrain [36], visual tracking [37], object tracking [38,39], etc.

### 2.2. Illumination estimation

For enhancing non-uniform illumination images, retinex [40] algorithm received much attention owing to its simplicity and effectiveness. As per retinex model, an image can be decomposed into two components, namely, (I) illumination (L), and (II) reflectance (R). The observed image (S) is represented by $S = L \times R$. For computational simplicity $S = L \times R$ is converted in logarithmic form $s = l + r$ or $r = s - l$, where $s = \log(S)$, $l = \log(L)$, and $r = \log(R)$. Reflectance (inherent property of an object) can be obtained by taking index form of $r = s - l$. The obtained index form is $R = \exp(s - l)$. Retinx algorithm uses the low-pass filter to estimate the illumination [41,42]. An effective method for estimating L is the key to illumination normalization based on Retinex theory [43].

To realize the photometric consistency, it is important to estimate the illumination of the real world environment. This estimation precision is enough to satisfy human perception. Various illumination estimation techniques are already widely reported in literature, such as:

(I) using human visual characteristics for AR [44],
(II) based on red chromaticity [45],
(III) using shadow borders [46], etc. Estimation techniques are also deployed in multiple application domains, such as:
(IV) deep outdoor illumination estimation [47],
(V) lighting virtual object in real scene using a single image [48],
(VI) urban scenes illumination estimation with the help of color matching [49],
(VII) real-time estimation techniques from faces for coherent rendering, etc [50],
(VIII) a real-time system for augmented reality on mobile devices to estimate of illumination direction [51], etc.

For illumination estimation, the Data Driven Estimation Methods (DDEMs) can be used [39]. DDEMs are of two types, namely, (I) unsupervised DDEMs, and (II) supervise DDEMs. Unsupervised DDEMs (fixed illumination estimation models based on certain hypotheses) are (I) GreyWorld (GW) [52], (II) maxRGB [53], (III) Shades of Grey (SoG) [54], and (IV) Edge-based method [55], etc. However, the supervised DDEMs (estimation models based on the color distribution and/or features training) are Color-by-Correlation (C-by-C) [56], Spatio-Spectral statistics-based method (Spatio-Spectral) [57], Neural Networks-based method (NN) [58], Support Vector Regression-based method (SVR) [59], Gamut Mapping [60], edge-based Gamut Mapping [61], etc.

Illumination colors of all the test images are computed using fixed DDEMs. The effectiveness of the assumed model (DDEMs) depends upon the distribution of colors of the test image.

To overcome the limitation of model fixing, image content analysis is deployed for illumination estimation in “Content Driven Estimation Methods” (CDEM). CDEMs are combinational methods [62], where several models are deployed on the same image followed by the best estimation technique or image’s content characteristics are combined with the outputs.

Optical properties of surfaces and the lighting conditions excluding reflected sources or shadows, are analyzed to measure surface intensity (Photometric flux per unit area or visible flux density is used to measure illuminance (I)).

## 3. Uneven illuminated imaging

Uneven illumination correction (at low magnification) is required for the images that are derived by shining light on two-dimensional objects [63]. No matter how evenly illuminated, vignetting (darkening at corners with a spotlit appearance) is introduced by the imaging devices or magnification tubes in all images. Various imaging techniques (segmentation, edge detection, etc.) and texture based feature extraction mechanism for unevenly illuminated images are discussed in these following sub-sections.

### 3.1. Uneven illuminated image segmentation

The performance of local threshold-based segmentation techniques for uneven illuminated images is highly sensitive to noise injection and the choice of initial window size for both fixed window method, or window merging technique. In [64] an adaptive thresholding based image segmentation technique, the window growing technique outperformed window merging techniques. The problem of background extraction and segmentation is reported in [65] using morphological transformations. In recent times, lots of work has been done in the area of unevenly illuminated image segmentation and background extraction. In [66], a non-local spatial information and intuitionistic fuzzy entropy based technique are reported. This method has the ability to decrease the influence of uneven lighting on images and injected noise. In [67], a dynamic window based on an incremental window growing approach achieved an excellent capability to handle a higher number of segmentation levels. In [68], a modified fuzzy C-means image segmentation is used for the same. The proposed technique obtained efficient results for uneven lighting segmenting the image by pattern, where biased intensity fields present.

### 3.2. Edge detection for uneven illuminated images

The main reasons for false edge detection in unevenly illuminated images are depth, surface normal vector, lighting and reflection discontinuousness. Background noise generated by the presence of a large obstacle, the noise of the imaging system is also responsible for the same. However, in dark image there is a high chance of edge information loss. In [69], wavelet similarity based technique is reported for edge detection from unevenly illuminated images. For edge detection of low illuminated images [70], a short step affine transformation Sobel algorithm is implemented. Comparison with one order and two order edge algorithms are also carried out. In [71], modeling and detection of blurred illumination edges are reported.

### 3.3. "Illumination-insensitive" texture feature extraction

Under different lighting conditions, the same surface texture looks dissimilar. The extracted feature set from the same surface under varying illumination is significantly different. Based on illumination compensation or enhancement, a texture-feature extraction methodology from the original surface [72] is applied, resulting in an "illumination-insensitive" [73] feature.

Geometric invariant classification of multispectral texture and Zernike moments of illumination is illustrated in [74]. Extraction of "illumination-invariant" features on the basis of natural images statistics are discussed in [75]. Illumination normalization on large and small scale features are reported in [76].

## 4. Uneven illumination correction

The intrinsic image is described by two pixel-wise multiplication techniques, namely, (I) illumination, and (II) reflectance. llumination and reflectance are required to correct the unevenness of illumination and visual quality enhancement of low local contrast image [77]. In literature, sereral techniques are already being reported to normalize uneven illumination and background correction. In this section, various normalization and correction techniques and their application area are discussed.

### 4.1. Uneven illumination normalization

Varying light is the major problem of uneven illumination. Uneven illumination normalization techniques without using training images and keeping the computational complexity low is always a challenging task [78,79]. Histogram equalization [80,81] is a technique to enhance the global contrast of an image and works fine only when the entire image is either dark or bright irrespective of backgrounds and foregrounds. To overcome this limitation, researchers have already reported various improved techniques [82], such as (I) block-based histogram equalization [83], (II) adaptive histogram equalization [84], (III) oriented local histogram equalization [85], and (IV) local normalization technology [86]. Logarithm Transforms [87], Gaussian mixture model [88], Power-law transformations [89], and contrast stretching transformation [90] are also widely used for the uneven illumination normalization purpose. Photometric normalization [91] based approaches, namely (I) single-scale retinex [92,93], (II) multi-scale retinex [94], (III) adaptive single scale retinex [95], (IV) homomorphic filtering [96], (V) single-scale self quotient image [97], (VI) multi-scale self quotient image [98], (VII) DCT-based normalization [99], and (VIII) wavelet-based normalization [69] are reported in the literature. Apart from illumination properties, all these techniques are based on human perception theory.

Application of histogram equalization, log transformation, and gamma correction [100] to rectify the uneven illumination problem of face recognition followed by the compression function in the retinal filter (COMP) is discussed.

Fast and easy DCT based techniques for illumination estimation and enhancement are reported for real-time systems in [101] and [102]. A discussion on linear and non-linear contrast enhancement techniques was addressed in [103]. In [104], presented a quotient image processing where different smoothing filter techniques are used to improve image quality in varying contrast condition. The proposed method is compared with morphological quotient image, self and dynamic quotient images. In [105], the same author proposed a framework based on 2D Gaussian illumination for contrast correction using the Quadtree technique (to locate low light region). A Fuzzy C-Means (FCM) reported in [106] for the reduction of low illumination. In [107], a multiplicative image formation models and Laplace interpolation and in [108] Weber's law were used for the same purpose. Local normalization methods depend on four main factors, namely, normal distribution (NORM), histogram equalization (HE), histogram matching (HM) and Gamma Intensity Correction (GIC) [109]. Multiscale illumination normalization using dual-tree complex wavelet transform in the logarithmic domain was presented in [110]. In order to preserve the mean brightness of an image, Singular Value Decomposition (SVD) was applied for low contrast enhancement techniques [111].

### 4.2. Uneven background correction

Pixel vignetting is a common problem for digital images captured by the sensors. The majority of the digital sensors are flat. Pixels present in the center of the sensor receive light rays directly (at an angle of 90 °), whereas the corner pixels receive the rays at a slight angle. The falloff pixel intensity from the center towards the edges of the image is commonly known as pixel vignetting.

Uneven illumination images are obtained using the following expression:

$$U_i\ (p,q)\ =\ I_i(p,q)\ +\ B(p,q) \tag{5}$$

where $U_i$ is the uneven illumination image, $I_i(p,q)$ is the same source image in ideal condition, and $B(p,q)$ is the extracted background image. Initially, the background image is generated using a low pass filter followed by subtracting from the source image to balance the contrast. Subtracted image is contrast starched to compensate for the effects produced by the earlier subtraction operation. Two types of background subtraction techniques, namely, prospective correction and retrospective correction are used for the correction of uneven illumination of an image (vignetting). It is assumed that the image composes a homogeneous background with a brighter or darker small object [112,113].

**a. Prospective Correction**

Prospective correction uses two different types of additional images acquired during image capturing. In the first category, images are obtained keeping the background without light (dark image) and the next category is the background with light after removal of the object (bright image). Number of images of these two categories are captured for the reduction of noise and attenuation of lighting defects [114–116]. Following transformation function is used to obtain a corrected image ($Corr_i$ $(p,q)$):

$$Corr_i(p,q) = \frac{o(p,q) - d(p,q)}{b(p,q) - d(p,q)}*C \tag{6}$$

here o($p,q$) is the source image, d($p,q$) and b($p,q$) represent the dark image and bright image, respectively. C is a normalization constant used for the purpose of recovering the source image color [117], which is computed as:

$$C = \frac{Mean(o(p,q)}{Mean(\frac{o(p,q) - d(p,q)}{b(p,q) - d(p,q)})} \tag{7}$$

The correction of a bright image (where the available image is the only bright image) depends upon the image acquisition device. The device can be linear or logarithmic with a gamma of 1. For a linear device, the corrected image is obtained using this following expressions:

$$Corr_i(p,q) = \frac{o(p,q)}{b(p,q)}*C \tag{8}$$

$$C = \frac{Mean(o(p,q)}{Mean(\frac{o(p,q)}{b(p,q)})} \tag{9}$$

For logarithmic devices, corrected images is obtained by subtracting the source image from the bright image.

For dark image, the correct expression is given by:

$$Corr_i(p,q) = o(p,q) - d(p,q) + mean(d(p,q)) \tag{10}$$

Perspective correction techniques are reported for document imaging in several studies. In [118], a perspective distortion correction approaches for document imaging (especially for uncalibrated images of documents) is reported. In [119], fuzzy sets and morphological operations based perspective distortion removal and recovering technique of front-parallel view of text with a single image are reported. In other work [120], finding a technique of distorting information and rectification of the prespective Chinese document images (without prior knowledge of imagepsilas edge and paragraphpsilas format) are reported. For correction of distorted images in documents, Chinese characterpsilas features of vertical strokes and horizontal characteristics of text line are implemented. The skew correction and perspective rectification in camera-based Farsi document images are described in [121].

**b. Retrospective Correction**

In the absence of additional image, an ideal illumination model is required for retrospective correction.

The technique is simple after removal of the object from the background (to generate the bright image) deployed prospective correction.

Various filtering techniques are used for retrospective correction, namely, (I) low-pass filter, (II) morphological filter, and (III) homomorphic filter. Apart from filtering techniques (IV) linear regression, and (V) surface fitting with polynomial is also used for the same.

(I) **Using Low-pass Filtering**

To compensate for illumination, background (low-pass filter with a very large kernel has used background estimation) is subtracted from the source image as the correct expression is given by:

$$Corr_i(p,q) = o(p,q) - LPF(o(p,q)) + mean(LPF(o(p,q)) \tag{11}$$

where LPF(o($p,q$) is the low pass filtered image (of the input image), and mean(LPF(o($p,q$))) is the mean of low pass filtered image.

- **Using Morphological Filtering**

In the morphological filtering method, two mathematical morphology operators are used to calculate the background, namely, (I) opening and (II) closing. The working principle of morphological filtering technique corresponds to top hat filtering process (black top hat for bright image and white top hat for dark background), where the high frequencies are removed keeping the low frequencies without change.

The following equations show the source image correction technique using a black top hat (BTH) as:

$$Corr_i(p, q) = BTH(o(p, q) + mean(clo\sin g(o(p, q)) \tag{12}$$

$$Corr_i(p, q) = (o(p, q) - clo\sin ng(o(p, q)) + mean(clo\sin g(o(p, q)) \tag{13}$$

- **Using Homomorphic Filtering**

The background is calculated using homomorphic filtering with a low-pass filter in the homomorphic filtering method. The following equation shows a source image correction technique using homomorphic filtering technique:

$$Corr_i(p, q) = \exp(LPF(\log(o(p, q))))*C \tag{14}$$

This logarithm of the source image passes through a low pass filter to remove the background and the exponent is used to restore the image.where C is a normalization coefficient, which is given by:

$$C = \frac{Mean(o(p, q)}{Mean(\frac{o(p,q)}{\exp(LPF(\log(o(p,q))))})} \tag{15}$$

- **Using Linear Regression**

The background is calculated utilizing the orthogonal linear regression in the linear regression method. The following eqn. shows a source image correction technique using linear regression techniques:

$$Corr_i(p, q) = o(p, q) - LR(o(p, q)) - mean(LR(o(p, q)) \tag{16}$$

where LR(o(*p*,*q*)) is the linear regression of the source image in *p* and *q*. Also, mean(LR(o(*p*,*q*)) is the mean of the same. This correction mechanism fails to work on a complex background.

- Using Surface Fitting with Polynomial

The background is calculated utilizing a minimum square fit of a polynomial in surface fitting with polynomial method (e.g.- second-order, Legendre, etc.). The background image is deducted from the source image to compensate for illumination.

The following eqn. shows source image correction technique using a surface fitting with polynomial technique (that approximates the background):

$$Corr_i(p, q) = o(p, q) - Poly(o(p, q)) - mean(Poly(o(p, q)) \tag{17}$$

where Poly(o(*p*,*q*) is a polynomial image of the source image in *p* and *q*. Also, mean(Poly(o(*p*,*q*)) is the mean of the polynomial image.

Respective correction techniques are more robust and desirable because the combined information across multiple images is used for illumination correction function (ICF) [122]. Color image correction is not possible by using the above mentioned techniques. The color image is converted into hue, saturation, lightness (HSV) color space, followed by deploying corrections on the lightness channel.

Retrospective correction is widely studied in medical imaging, especially MR Imaging. Studying adiabatic magnetic resonance imaging sequence, an automatic retrospective correction mechanism of intensity variations observed in a high-resolution surface coil MR image of the rat brain is presented in [123]. In [124], a simple image-based technique for retrospective correction of physiological motion effects in fMRI is presented. The problem of retrospective correction of intensity inhomogeneity in MR images is addressed in [125]. An optimization framework is used to minimize the information of the corrected image, keeping the global intensity statistic preserved. In [126], retrospective correction of intensity inhomogeneities due to the heel effect in digital radiographs is reported. In a recent work [127], a Generative Adversarial Networks (GANs) based retrospective correction is proposed for rigid and non-rigid MR motion artifacts. In addition, a diffusion tensor imaging emerges from coil combination mode is reported for bias correction in [128].

### *4.3. Shadow removal*

Presence of shadows leads to quality degradation of images and cause image interpretation problem [129]. To recover illumination field, three different types of shadow removal techniques are used in literature to preserve the texture well and keep the shadow boundary smooth, namely, (I) model-based shadow removal, (I) additive shadow removal, and (III) combined shadow removal [130].

**a. Model-based shadow removal**

Two types of light sources, viz., direct and ambient light, are used in model-based shadow removal technique. The term ‘direct light’ is self-explanatory, while the reflected light from surrounding surfaces is termed as the ‘ambient light’. The entire direct light or part of it is occluded for the shadow areas.

**b. Additive shadow removal**

The difference to the pixels in the shadow areas is added to compute the average pixel intensities in the shadow and lit areas of the image.

**c. Combined shadow removal**

It is a hybrid technique of the previously mentioned two techniques. The initial step involves conversion of the image to the YCbCr color-space. Then, correction on the Y channel is carried out followed by correction of Cb and Cr channels by model-based method. Preservation of chromaticity in cases when shadow covers most of the background with effective change in brightness is well documented in [131,132].

To compute normalized RGB for both foreground and corresponding background, single Gaussian is used and even for background modelling. Comparison between the two is also carried out to evaluate their similarity index.

Selection of gradient directions of each dark pixel from the foreground using a designated threshold is addressed in [133]. Computation of the corresponding background pixel is carried out and it is eliminated based on the same shadow.

Proposed technique works fine when the texture component of the background is strong. Evaluation of color similarity between foreground and background (considered a shadow, if similar), calculation of normalized cross-correlation among foreground colors and its corresponding background is done by implementing HIS color model.Mixture of Gaussians (MOG) technique with minor modifications for background modelling was reported in [134,135]. Classification of a pixel as an object or background depends on its chromaticity component. If the chromaticity component of a foreground pixel is high enough, then it is classified as an object pixel and is considered as background if the pixel is dark.

## 5. Applications of illumination correction methods

Illumination correction methods are used in wide application domains. In this section, correction methods implemented for remote sensing images, medical imaging modalities, underground imaging and document imaging are reported.

### *5.1. Remote sensing images*

Presence of thin clouds, mountainous terrain, atmospheric conditions, topographic positions, etc., lead to uneven illumination of remotely sensed images. In recent times several works have been reported in this area. In the mountainous terrain, differential terrain illumination is observed in satellite imaging. Varying in reflectance of similar ground feature results misclassification of land cover classes because of its different topographic positions. Correction techniques of satellite images were reported in [136], where the distortion is caused by differential terrain illumination. The removal of effect of thin clouds to restore normal color of ground objects by applying an efficient uneven illumination correction algorithm was illustrated in [137].

Remote sensing of vegetation is severely affected by steep hill and mountain slopes. Correction techniques of satellite imagery required for operational or time-critical applications were reported in [138] and [139]. The former discusses variance of reflectance and illumination with topography, whereas the latter addressed the normalization of varying illumination and atmospheric conditions in remotely sensed images.

Radiometric processing of aerial and satellite remote-sensing imagery is addressed in [140]. Case study is reported from southwestern Yukon, Canada, where the obtained accuracy and utility of this model have been tested in the automated terrain analysis of its moderate to the high relief environment. Another case study of a moderately sloped area where comparison of illumination geometry-based methods for topographic correction of QuickBird satellite images has been carried out is discussed in [141].

### *5.2. Medical images*

#### *5.2.1. Retinal images*

Computer-assisted diagnosis of ophthalmic disorders is studied from retinal images captured by advanced fundus camera. High-quality color digital images captured by camera delivers severely distorted resultant images as the retinal surface light reflection exhibits local luminosity and contrast variability during the acquisition process. Estimation and correction techniques for luminosity variation in retinal images are discussed in [142].

A background normalizing technique using between low pass and Gaussian filtering is reported in [143]. Dehazing for retinal vessel segmentation using Convolutional Neural Networks (CNN) is reported in [144]. Correction technique using Laplace interpolation is addressed in [145]. Retrospective illumination correction of retinal images is reported in [146]. Contrast equalization and illumination correction in for colour fundus images addressed in [147–150].

#### *5.2.2. Microscopy images*

Many digital microscopy images suffer from inhomogeneity due to uneven illumination (because of misaligned optics, dust, non-uniform light sources and vignetting [151], etc.) or camera nonlinearity commonly known as shading artifacts. The actual measurements and the right perception of the sample image can alter the intensity inhomogeneity of the stitched images. The quality improvement is reported using flat-field correction technique (Vignetting function) in [152]. In [153], three methods for retrospective correction of vignetting on medical microscopy images is reported. The reported techniques are compared with a prospective correction method. Two new retrospective shading correction algorithms for whole slide image (WSI) is addressed in [154]. The common forms of WSI are namely, (I) multiple image tiles before mosaicking, and (II) an already-stitched image. Mosaicking artifacts in multimodal images for illumination correction is presented in [155], and a fully convolutional network for dermoscopy image illumination correction is reported in [156]. High throughput microscopic image illumination correction is presented in [157].

#### 5.2.3. Magnetic resonance images

Magnetic Resonance images [158–161] produced by old MRI machines are corrupted by bias field signal (low-frequency) and very smooth signal [162]. The authors in [163] stated the spatial sensitivity profile of the surface coil from the original anatomical image. In addition, the normalization technique was discussed in [164]. Both [165] and [166] deal with intensity inhomogeneities in which knowledge of tissue properties is applied. While the former deals with correction of intensity inhomogeneities, whereas the latter addresses a parametric estimate of intensity inhomogeneities applied to MRI. Radiofrequency inhomogeneity correction on the reproducibility of intracranial volumes is addressed in [167]. The authors in [168] and [169] addressed the study of an automatic intensity-correction algorithm for high-resolution MR imaging of the human brain, by using phased array detectors. MR grayscale inhomogeneity correction using optimized homomorphic unsharp masking is addressed in [170].

The degree of uneven illumination distortion during medical image acquisition are suggested to be abandoned or re-acquired to ensure the reliability of computed aided diagnosis results.

### 5.3. Underwater images

When light travels in water, it gets absorbed and scattered. Three major difficulties exist for underwater imaging, namely, (I) color cast, (II) under-exposure, and (III) fuzz. In [171], the authors proposed using color correction and illumination adjustment to achieve a new technique of underwater image enhancement.

In [172], color correction of underwater images and in [173] a nonuniform illumination correction technique for underwater images is reported using the maximum likelihood estimation method. Dehazing technique used for the underwater image enhancement resulting in minimum loss of information and histogram distribution has been stated in [174]. Howerver, in [175] the same technique with wavelength compensation is addressed.

In a very recent study, underwater image restoration is presented using Convolutional Neural Network [176].

### 5.4. Document imaging

Document image recognition by OCR is highly affected by under condition of uneven illumination. A Retinex-based illumination correction method was proposed to resolve it in [177]. In [178], of the authors used convex hulls in nonparametric illumination correction for scanned document images. An adaptive correction technique is presented in the nonuniform illumination of multispectral digital images.

Apart from these, there are many areas where illumination corrections are widely used (e.g. fisheye imaging [179], ground-based astronomical Image [180], endoscopic camera [181], object tracking for video processing [182–186] etc.)

## 6. Objective assessment

To evaluate the enhancement results, three objective metrics namely, (I) RMS contrast [187], (II) discrete entropy [188], and (III) lightness of error (LOE) [189] are used.

### 6.1. RMS contrast

Contrast makes an object distinguishable from others. RMS contrast is represented as:

$$\text{Contrast}_{\text{RMS}} = \sqrt{\frac{1}{MN}\sum_{i=0}^{N-1}\sum_{j=o}^{M-1}\{I(i,j) - \bar{I}\}^2}$$

where $I(i,j)$ is the normalized intensity of pixel from 0 to 1 at the position $(i,j)$. $\bar{I}$ is the average intensity [190–193].

### 6.2. Discrete entropy

Entropy is the amount of information contained in an image. Flat images have zero entropy, whereas image containing heavy objects has high entropy value [194]. Entropy is represented as:

$$\text{H} = -\sum_i P_i \log_2 P_i$$

where $P_i$ is the probability between two adjacent pixel differences is $i$.

### 6.3. Lightness of error (LOE)

Small Lightness of Error (LOE) represents [195] better naturalness preservation. The lightness *L(x,y)* of an image is given as the maximum of its three color channels:

$$L_{(x,y)} = \max_{c\in[r,g,b]} I^c(x, y) \tag{18}$$

For each pixel (x,y), the relative order difference (ROD) of the lightness between the original image *I* and its enhanced version $I_e$ is defined as follows:

$$ROD_{(x,y)} = \sum\nolimits_{i=1}^{m} \sum\nolimits_{j=1}^{n} (U(L(x, y), L(i, j)) \oplus U(L_e(i, j))) \tag{19}$$

$$\mathrm{U}(x, y) =_0^1 \ {}^{for x > y}_{else} \tag{20}$$

where *m* and *n* are the height and width, U(*x,y*) is the unit step function and ⊕ is the operator. The LOE measure is demarcated as:

$$LOE = \frac{1}{m^*n} \sum_{i=1}^{m} \sum_{j=1}^{n} RD(i, j) \tag{21}$$

Natural stimuli and efficiency calculations is the use for RMS contrast [196–198]. To characterize original and enhanced images, discrete entropy (a statical measure of randomness) is deployed in [199]. In [62,200], LOE is used to access naturalness preservation objectively.

## 7. Conclusion

Reduction of variations in illumination or their entire elimination (for ease of use in industrial settings) can be achieved in the implementation of appropriate image processing techniques before level-sensitive processing. In this study, many of the state-of-the-art methods for non-uniform illumination correction, background correction techniques, and shadow correction, are reported. Besides this, various illumination models, estimation, unevenly illuminated image processing are also discussed.

This review study of the reported analyses done by implementing various image processing techniques reveals that there is ample scope to study and propose hardware considerations for performing correction techniques in real-time systems.

## Conflict of interest statement

No conflict of interest.

## References


[1] Y. Wang, W. Tan, S.C. Lee, Illumination normalization of retinal images using sampling and interpolation, Medical Imaging 2001: Image Processing vol. 4322, (2001) 500–508.
[2] Q. Huang, W. Gao, W. Cai, Thresholding technique with adaptive window selection for uneven lighting image, Pattern Recognit. Lett. 26 (6) (2005) 801–808.
[3] R. Saini, M. Dutta, Image segmentation for uneven lighting images using adaptive thresholding and dynamic window based on incremental window growing approach, Int. J. Comput. Appl. 56 (13) (2012).
[4] Z. Lei, H. Gang, X. Dongmei, W. Haitao, Edge detection algorithm for uneven lighting image based on vision theory, Computational Intelligence and Natural Computing, 2009. CINC'09. International Conference on vol. 1, (2009) 182–185.
[5] T. Chen, W. Yin, X.S. Zhou, D. Comaniciu, T.S. Huang, Illumination normalization for face recognition and uneven background correction using total variation based image models, Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on 2 (2005) 532–539.
[6] Y. Chen, J. Yang, H. Shu, L. Shi, J. Wu, 2-d impulse noise suppression by recursive GaussianMaximum likelihood estimation, PLoS One 9 (5) (2014) 1–14 e96386.
[7] B. Zhong, X. Yuan, R. Ji, Y. Yan, Z. Cui, et al., Structured Partial Least Squares for SimultaneousObject Tracking and Segmentation, Elsevier Neurocomputing, 2014, pp. 317–327.
[8] Z. Lian, J. Song, Y. Li, Adaptive illumination normalization approach based on denoising technique for face recognition, J. Shanghai Jiaotong Univ. 22 (1) (2017) 45–49.
[9] A. Delalleau, J.M. Lagarde, J. George, An a priori shading correction technique for contact imaging devices, IEEE Trans. Image Process. 20 (10) (2011) 2876–2885.
[10] P. Roy, S. Goswami, S. Chakraborty, A.T. Azar, N. Dey, Image segmentation using rough set theory: a review, Int. J. Rough Sets Data Anal. (IJRSDA) 1 (2) (2014) 62–74.
[11] N. Dey, A.B. Roy, M. Pal, A. Das, FCM based blood vessel segmentation method for retinal images, arXiv preprint arXiv:1209.1181 (2012).
[12] S. Samantaa, N. Dey, P. Das, S. Acharjee, S.S. Chaudhuri, Multilevel threshold based gray scale image segmentation using cuckoo search, arXiv preprint arXiv:1307.0277 (2013).
[13] S. Hore, S. Chakraborty, S. Chatterjee, N. Dey, A.S. Ashour, L.V. Chung, D.N. Le, An integrated interactive technique for image segmentation using stack based seeded region growing and thresholding, Int. J. Electr. Comput. Eng. 6 (6) (2016) 2773–2780.
[14] S. Samanta, S. Acharjee, A. Mukherjee, D. Das, N. Dey, Ant weight lifting algorithm for image segmentation, 2013 IEEE International Conference on Computational Intelligence and Computing Research (2013) 1–5.
[15] N. Dey, V. Rajinikanth, A. Ashour, J.M. Tavares, Social group optimization supported segmentation and evaluation of skin melanoma images, Symmetry 10 (2) (2018) 51.
[16] J. Chaki, N. Dey, L. Moraru, F. Shi, Fragmented plant leaf recognition: bag-of-features, fuzzy-color and edge-texture histogram descriptors with multi-layer perceptron, Optik 181 (2019) 639–650.
[17] N. Dey, B. Nandi, A.B. Roy, D. Biswas, A. Das, S.S. Chaudhuri, Analysis of Blood Cell Smears Using Stationary Wavelet Transform & Harris Corner Detection. Published by Recent Advances in Computer Vision and Image Processing: Methodologies and Applications, (2013), pp. 357–370.

[18] J. Chaki, N. Dey, A Beginner's Guide to Image Preprocessing Techniques, CRC Press, 2018.
[19] S. Sghaier, W. Farhat, C. Souani, Novel technique for 3D Face Recognition using anthropometric methodology, Int. J. Ambient. Comput. Intell. 9 (1) (2018) 60–77.
[20] B. Chakraborty, S. Bhattacharyya, S. Chakraborty, Generative model based video shot boundary detection for automated surveillance, Int. J. Ambient. Comput. Intell. 9 (4) (2018) 69–95.
[21] K. Sharma, J. Virmani, A decision support system for classification of normal and medical renal disease using ultrasound images: a decision support system for medical renal diseases, Int. J. Ambient. Comput. Intell. 8 (2) (2017) 52–69.
[22] L. Moraru, S. Moldovanu, A.L. Culea-Florescu, D. Bibicu, A.S. Ashour, N. Dey, Texture analysis of parasitological liver fibrosis images, Microsc. Res. Tech. 80 (8) (2017) 862–869.
[23] Y. Wang, F. Shi, L. Cao, N. Dey, Q. Wu, A.S. Ashour, L. Wu, Morphological segmentation analysis and texture-based support vector machines classification on mice liver fibrosis microscopic images, Curr. Bioinform. (2018).
[24] L. Moraru, S. Moldovanu, L.T. Dimitrievici, A.S. Ashour, N. Dey, Texture anisotropy technique in brain degenerative diseases, Neural Comput. Appl. 30 (5) (2018) 1667–1677.
[25] J. Chaki, N. Dey, F. Shi, R.S. Sherratt, Pattern mining approaches used in sensor-based biometric recognition: a review, IEEE Sens. J. (2019).
[26] J.M. Van Verth, L.M. Bishop, Essential Mathematics for Games and Interactive Applications: a Programmer's Guide, CRC Press, 2008.
[27] S. Zhukov, A. Iones, G. Kronin, An ambient light illumination model, Rendering Techniques' 98, Springer, Vienna, 1998, pp. 45–55.
[28] J. Stam, An illumination model for a skin layer bounded by rough surfaces, Rendering Techniques 2001, Springer, Vienna, 2001, pp. 39–52.
[29] G. Kay, T. Caelli, Inverting an illumination model from range and intensity maps, CVGIP Image Underst. 59 (2) (1994) 183–201.
[30] G. Kay, T. Caelli, Estimating the parameters of an illumination model using photometric stereo, Graph. Model. Image Process. 57 (5) (1995) 365–388.
[31] P.M. Novotny, N.J. Ferrier, Using infrared sensors and the Phong illumination model to measure distances, Proceedings. 1999 IEEE International Conference on Robotics and Automation, 1999 2 (1999) 1644–1649.
[32] J. Lee, B. Moghaddam, H. Pfister, R. Machiraju, A Bilinear Illumination Model for Robust Face Recognition, Institute of Electrical and Electronics Engineers, 2005.
[33] T. Zhang, Y.Y. Tang, B. Fang, Z. Shang, X. Liu, Face recognition under varying illumination using gradientfaces, IEEE Trans. Image Process. 18 (11) (2009) 2599–2606.
[34] C. Gontikakis, J.M. Hameury, Constraints on the illumination model for soft X-ray transients, Astron. Astrophys. 271 (1993) 118.
[35] S. Bhardwaj, T. Ozcelebi, R. Verhoeven, J. Lukkien, Smart indoor solid state lighting based on a novel illumination model and implementation, IEEE Trans. Consum. Electron. 57 (4) (2011) 1612–1621.
[36] S. Sandmeier, K.I. Itten, A physically-based model to correct atmospheric and illumination effects in optical satellite data of rugged terrain, IEEE Trans. Geosci. Remote. Sens. 35 (3) (1997) 708–717.
[37] A. Kale, C. Jaynes, A joint illumination and shape model for visual tracking, Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on 1 (2006) 602–609.
[38] D. Koller, K. Daniilidis, H.H. Nagel, Model-based object tracking in monocular image sequences of road traffic scenes, Int. J. Comput. 11263on 10 (3) (1993) 257–281.
[39] B. Li, W. Xiong, W. Hu, H. Peng, Illumination estimation based on bilayer sparse coding, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, (2013), pp. 1423–1429.
[40] L. Wang, L. Xiao, H. Liu, Z. Wei, Variational Bayesian method for retinex, IEEE Trans. Image Process. 23 (8) (2014) 3381–3396.
[41] E. Land, J. Mccann, Lightness and retinex theory, J. Opt. Soc. Am. 61 (61) (1971) 1–11.
[42] Z. Rao, T. Xu, J. Luo, J. Guo, G. Shi, H. Wang, Non-uniform illumination endoscopic imaging enhancement via anti-degraded model and L 1 L 2-based variationalretinex, EURASIP J. Wirel. Commun. Netw. 2017 (1) (2017) 205.
[43] J. Yi, X. Mao, L. Chen, Y. Xue, A. Rovetta, C.D. Caleanu, Illumination normalization of face image based on illuminant direction estimation and improved retinex, PLoS One 10 (4) (2015) e0122200.
[44] Y. Oyama, H. Takahashi, Illumination estimation based on human visual characteristics for AR, 2018 International Workshop on Advanced Image Technology (IWAIT) (2018) 1–4.
[45] N. Banić, S. Lončarić, Using the red chromaticity for illumination estimation, 2015 9th International Symposium on Image and Signal Processing and Analysis (ISPA) (2015) 131–136.
[46] A. Panagopoulos, T.F.Y. Vicente, D. Samaras, Illumination estimation from shadow borders, 2011 IEEE International Conference on Computer Vision Workshops (ICCV Workshops) (2011) 798–805.
[47] Y. Hold-Geoffroy, K. Sunkavalli, S. Hadap, E. Gambaretto, J.F. Lalonde, Deep outdoor illumination estimation, IEEE International Conference on Computer Vision and Pattern Recognition 2 (2017).
[48] X. Chen, K. Wang, X. Jin, Single image based illumination estimation for lighting virtual object in real scene, 2011 12th International Conference on Computer-Aided Design and Computer Graphics (CAD/Graphics) (2011) 450–455.
[49] M. Sun, G. Schindler, G. Turk, F. Dellaert, Color matching and illumination estimation for urban scenes, IEEE International Workshop on 3-D Digital Imaging and Modeling (2009).
[50] S.B. Knorr, D. Kurz, Real-time illumination estimation from faces for coherent rendering, 2014 IEEE International Symposium on Mixed and Augmented Reality (ISMAR) (2014) 349–350.
[51] I. Arief, S. McCallum, J.Y. Hardeberg, Realtime estimation of illumination direction for augmented reality on mobile devices, Color and Imaging Conference 2012 (1) (2012) 111–116.
[52] G. Buchsbaum, A spatial processor model for object colourperception, J. Franklin Inst. 310 (1) (1980) 337–350.
[53] E.H. Land, The retinex theory of color vision, Sci. Am. 237 (6) (1977) 108–128.
[54] G. Finlayson, E. Trezzi, Shades of gray and color constancy, Proc. of IS&T/SID Color Imaging Conference, (2004), pp. 37–41.
[55] J.V. Weijer, T. Gevers, A. Gijsenij, Edge-based color constancy, IEEE TIP 16 (9) (2007) 2207–2214.
[56] G. Finlayson, S. Hordley, P. Hubel, Color by correlation:a simple, unifying framework for color constancy, IEEE TPAMI 22 (11) (2001) 1209–1221.
[57] A. Chakrabarti, K. Hirakawa, T. Zickler, Color constancywith spatio-spectral statistics, IEEE TPAMI 34 (8) (2012) 1509–1519.
[58] V. Cardei, B. Funt, K. Barnard, Estimating the scene illumination chromaticity using a neural network, JOSA A 19 (12) (2002) 2374–2386.
[59] W. Xiong, B. Funt, Estimating illumination chromaticityvia support vector regression, J. Imaging Sci. Technol. 50 (4) (2006) 341–348.
[60] A. Gijsenij, T. Gevers, J.V. Weijer, Generalized gamut mapping using image derivative structuresfor color constancy, IJCV 86 (2) (2010) 127–139.
[61] B. Li, W. Xiong, W. Hu, Evaluating combinational colorconstancy methods on real-world images, Proc. of CVPR, (2011), pp. 1929–1936.
[62] S. Wang, J. Zheng, H.M. Hu, B. Li, Naturalness preserved enhancement algorithm for non-uniform illumination images, IEEE Trans. Image Process. 22 (9) (2013) 3538–3548.
[63] J. Sedgewick, Scientific Imaging with Photoshop: Methods, Measurement, and Output, Peachpit Press, 2010.
[64] S.S. Pradhan, D. Patra, P.K. Nanda, Adaptive thresholding based image segmentation with uneven lighting condition, IEEE Region 10 and the Third International Conference on Industrial and Information Systems, 2008. ICIIS 2008 (2008) 1–6.
[65] S.S. Jambhorkar, S.S. Gornale, V.T. Humbe, R.R. Manza, K.V. Kale, Uneven background extraction and segmentation of good, normal and bad quality fingerprint images, ADCOM 2006. International Conference on Advanced Computing and Communications, 2006 (2006) 222–225.
[66] H. Yu, J. Fan, A novel segmentation method for uneven lighting image with noise injection based on non-local spatial information and intuitionistic fuzzy entropy, EURASIP J. Adv. Signal Process. 2017 (1) (2017) 74.
[67] R. Saini, M. Dutta, Image segmentation for uneven lighting images using adaptive thresholding and dynamic window based on incremental window growing approach, Int. J. Comput. Appl. 56 (13) (2012).

[68] L. Ma, R.C. Staunton, A modified fuzzy C-means image segmentation algorithm for use with uneven illumination patterns, Pattern Recognit. 40 (11) (2007) 3005–3011.
[69] A. Swaminathan, S.S.K. Ramapackiyam, Edge detection for illumination varying images using wavelet similarity, IET Image Process. 8 (5) (2014) 261–268.
[70] Y. Dou, K. Hao, Y. Ding, A short step affine transformation Sobel algorithm based image edge detection in low illumination, Chinese Automation Congress (CAC), 2015 (2015) 594–597.
[71] C. Wen, C.H. Huang, K.C. Chang, Modeling and detection of blurred illumination edges, 2010 Fourth Pacific-Rim Symposium on Image and Video Technology (2010) 276–281.
[72] M. Jian, K.M. Lam, J. Dong, Illumination-insensitive texture discrimination based on illumination compensation and enhancement, Inf. Sci. 269 (2014) 60–72.
[73] J. Zhang, X. Xie, A study on the effective approach to illumination-invariant face recognition based on a single image, Chinese Conference on Biometric Recognition (2012) 33–41.
[74] L. Wang, G. Healey, Using Zernike moments for the illumination and geometry invariant classification of multispectral texture, IEEE Trans. Image Process. 7 (2) (1998) 196–203.
[75] L.H. Chen, Y.H. Yang, C.S. Chen, M.Y. Cheng, Illumination invariant feature extraction based on natural images statistics—Taking face images as an example, 2011 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2011) 681–688.
[76] X. Xie, W.S. Zheng, J. Lai, P.C. Yuen, Face illumination normalization on large and small scale features, CVPR 2008. IEEE Conference on Computer Vision and Pattern Recognition, 2008 (2008) 1–8.
[77] W. Wang, C. He, L. Tang, Z. Ren, Total variation based variational model for the uneven illumination correction, Neurocomputing 281 (2018) 106–120.
[78] Y. Luo, Y.P. Guan, C.Q. Zhang, A robust illumination normalization method based on mean estimation for face recognition, ISRN Mach. Vis. 2013 (2013).
[79] V. Truc, N. Paveić, Gabor-based kernel partial-least-squares discrimination features for face recognition, Informatica 20 (1) (2009) 115–138.
[80] S.M. Pizer, E.P. Amburn, J.D. Austin, R. Cromartie, A. Geselowitz, T. Greer, et al., Adaptive histogram equalization and its variations, Comput. Vis. Graph. Image Process. 39 (1987) 355–368.
[81] M.F. Khan, E. Khan, Z.A. Abbasi, Image contrast enhancement using normalized histogram equalization, Opt. – Int. J. Light Electron. Opt. 126 (24) (2015) 4868–4875.
[82] J. Yi, X. Mao, L. Chen, Y. Xue, A. Rovetta, C.D. Caleanu, Illumination normalization of face image based on illuminant direction estimation and improved retinex, PLoS One 10 (4) (2015) e0122200.
[83] X. Xie, K. Lam, Face recognition under varying illumination based on a 2D face shape model, Pattern Recognit. 38 (2) (2005) 221–230.
[84] V.P. Vishwakarma, S. Pandey, M.N. Gupta, Adaptive histogram equalization and logarithm transform with rescaled low frequency DCT coefficients for illumination normalization, Int. J. Recent. Trends Eng. Res. 1 (1) (2009) 318–322.
[85] P.H. Lee, S.W. Wu, Y.P. Hung, Illumination compensation using oriented local histogram equalization and its application to face recognition, IEEE Trans. Image Process. 21 (9) (2012) 4280–4289.
[86] X. Xie, K. Lam, An efficient method for face recognition under varying illumination, Proc. IEEE International Symposium on Circuits and Systems 4 (2005) 3841–3844.
[87] M. Savvides, B.V. Kumar, Illumination normalization using logarithm transforms for face authentication, International Conference on Audio-and Video-Based Biometric Person Authentication (2003) 549–556.
[88] K. K. Mohanty, M. K. Gellaboina, & J. C. Wilson, (2012). U.S. Patent No. 8,150,202. Washington, DC: U.S. Patent and Trademark Office.
[89] C.C. Chude-Olisah, G. Sulong, U.A. Chude-Okonkwo, S.Z. Hashim, Illumination normalization for edge-based face recognition using the fusion of RGB normalization and gamma correction, 2013 IEEE International Conference on Signal and Image Processing Applications (ICSIPA) (2013) 412–416.
[90] M. Foracchia, E. Grisan, A. Ruggeri, Luminosity and contrast normalization in retinal images, Med. Image Anal. 9 (3) (2005) 179–190.
[91] M. Leszczyński, Image preprocessing for illumination invariant face verification, J. Telecommun. Inf. Technol. (2010) 19–25.
[92] E. Land, J. McCann, Lightiness and retinex theory, J. Opt. Soc. America 61 (1971) 1–11.
[93] D.J. Jobson, Z. Rahman, G.A. Woodell, Properties and performance of a center/surround retinex, IEEE Trans. Image Process. 6 (3) (1997) 451–462.
[94] Z. Rahman, G. Woodell, D. Jobson, A comparison of the multiscaleretinex with other image enhancement techniques, Proc. 50th IS&T Anniv. Conf. (1997).
[95] Y.K. Park, S.L. Park, J.K. Kim, Retinex method based on adaptive smoothing for illumination invariant face recognition, Signal Process. 88 (8) (2008) 1929–1945.
[96] R. Gonzalez, R. Woods, Digital Image Processing, 2nd ed., Addison-Wesley Longman, Boston, 1992.
[97] H. Wang, S.Z. Li, Y. Wang, Face recognition under varying lighting condition using self quotient image, Proc. 6th IEEE Int. Conf. Autom. Face Gesture Recog. (2004) 819–824.
[98] H. Wang, S.Z. Li, Y. Wang, J. Zhang, Self quotient image for face recognition, ICIP'04. 2004 International Conference on Image Processing, 2004 2 (2004) 1397–1400.
[99] V. Štruc, N. Pavešic, Photometric normalization techniques for illumination invariance, in: Y.J. Zhang (Ed.), Advances in Face Image Analysis: Techniques and Technologies, IGI Global, 2011, pp. 279–300.
[100] Ahmed Salah-ELDin, Khaled Nagaty, Taha ELArif, An enhanced histogram matching approach using the retinal filter's compression function for illumination normalization in face recognition, International Conference Image Analysis and Recognition (2008) 873–883.
[101] Virendra P. Vishwakarma, Sujata Pandey, M.N. Gupta, A novel approach for face recognition using DCT coefficients re-scaling for illumination normalization, ADCOM 2007. International Conference on Advanced Computing and Communications, 2007 (2007) 535–539.
[102] Zhichao Lian, Meng JooEr, Juekun Li, A novel local illumination norma lization approach for face recognition, International Symposium on Neural Networks (2011) 350–355.
[103] Salem Saleh Al-amri, N.V. Kalyankar, S.D. Khamitkar, Linear and non-linear contrast enhancement image, Int. J. Comput. Sci. Netw. Secur. 10 (2) (2010) 139–143.
[104] Yu Cheng, Zhigang Jin, Cunming Hao, Illumination normalization based on different smoothing filters quotient image, 2010 3rd International Conference on Intelligent Networks and Intelligent Systems (ICINIS) (2010) 28–31.
[105] Yu Cheng, Zhigang Jin, Cunming Hao, Illumination normalization based on 2D Gaussian illumination model, 2010 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE) 3 (2010) V3–451.
[106] Marios Dimitrios Vlachos, Evangelos Spyros Dermatas, Non-uniform illumination correction in infrared images based on a modified fuzzy c-means algorithm, J. Biomed. Graph. Comput. 3 (1) (2013) 6–19.
[107] Conor Leahy, Andrew O'Brien, Chris Dainty, Illumination correction of retinal images using Laplace interpolation, Appl. Opt. 51 (35) (2012) 8383–8389.
[108] Biao Wang, Weifeng Li, Wenming Yang, Qingmin Liao, Illumination normalization based on Weber's law with application to face recognition, IEEE Signal Process. Lett. 18 (8) (2011) 462–465.
[109] Mauricio Villegas Santamaría, Roberto Paredes Palacios, Comparison of Illumination Normalization Methods for Face Recognition, Work. Biometrics Internet, 2005, pp. 27–30.
[110] Haifeng Hu, Multiscale illumination normalization for face recognition using dual-tree complex wavelet transform in logarithm domain, Comput. Vis. Image Underst. 115 (10) (2011) 1384–1394.
[111] R. Atta, R.F. Abdel-Kader, Brightness preserving based on singular value decomposition for image contrast enhancement, Opt. – Int. J. Light Electron. Opt. 126 (7-8) (2015) 799–803.
[112] John C. Russ, The Image Processing Handbook, fifth edition, CRC Press, 2006.
[113] Y. Zheng, S. Lin, C. Kambhamettu, J. Yu, S.B. Kang, Single-image vignetting correction, IEEE Trans. Pattern Anal. Mach. Intell. 31 (12) (2009) 2243–2256.
[114] L. Jagannathan, C.V. Jawahar, August). Perspective correction methods for camera based document analysis, Proc. First Int. Workshop on Camera-Based Document Analysis and Recognition, (2005), pp. 148–154.
[115] D. Pavić, V. Schönefeld, L. Kobbelt, Interactive image completion with perspective correction, Vis. Comput. 22 (9–11) (2006) 671–681.

[116] R. Baumann, C. Blackwell, W.B. Seales, Automatic perspective correction of manuscript images, International Conference on Asian Digital Libraries (2012) 11–18.
[117] https://clouard.users.greyc.fr/Pantheon/experiments/illumination-correction/index-en.html#prospective (Accessed 7 February 2019).
[118] R. Baumann, C. Blackwell, W.B. Seales, Automatic perspective correction of manuscript images, International Conference on Asian Digital Libraries (2012) 11–18.
[119] S. Lu, B.M. Chen, C.C. Ko, Perspective rectification of document images using fuzzy set and morphological operations, Image Vis. Comput. 23 (5) (2005) 541–553.
[120] W. Zhang, X. Li, X. Ma, Perspective correction method for Chinese document images, IITAW'08. International Symposium on Intelligent Information Technology Application Workshops, 2008 (2008) 467–470.
[121] M. Golpardaz, H. Nezamabadi-Pour, Perspective rectification and skew correction in camera-based farsi document images, Machine Vision and Image Processing (MVIP), 2011 7th Iranian (2011) 1–5.
[122] S. Singh, M.A. BRAY, T.R. Jones, A.E. Carpenter, Pipeline for illumination correction of images for high throughput microscopy, J. Microsc. 256 (3) (2014) 231–236.
[123] B.D. Ross, P. Bland, M. Garwood, C.R. Meyer, Retrospective correction of surface coil MR images using an automatic segmentation and modeling approach, NMR Biomed. 10 (3) (1997) 125–128.
[124] G.H. Glover, T.Q. Li, D. Ress, Image-based method for retrospective correction of physiological motion effects in fMRI: RETROICOR, Magn. Reson. Med. 44 (1) (2000) 162–167.
[125] B. Likar, M.A. Viergever, F. Pernus, Retrospective correction of MR intensity inhomogeneity by information minimization, IEEE Trans. Med. Imaging 20 (12) (2001) 1398–1410.
[126] G. Behiels, F. Maes, D. Vandermeulen, P. Suetens, Retrospective correction of the heel effect in hand radiographs, Med. Image Anal. 6 (3) (2002) 183–190.
[127] K. Armanious, T. Küstner, K. Nikolaou, S. Gatidis, B. Yang, Retrospective correction of rigid and non-rigid MR motion artifacts using GANs, arXiv preprint arXiv:1809.06276 (2018).
[128] K. Sakaie, M. Lowe, Retrospective correction of bias in diffusion tensor imaging arising from coil combination mode, Magn. Reson. Imaging 37 (2017) 203–208.
[129] S. Luo, H. Li, H. Shen, Shadow removal based on clustering correction of illumination field for urban aerial remote sensing images, 2017 IEEE International Conference on Image Processing (ICIP) (2017) 485–489.
[130] http://www.inf.u-szeged.hu/projectdirs/ssip2011/teamF/ (Accessed 14 February 2019).
[131] J.M. Stephen, J. Sumer, D. Zoran, Tracking groups of people, Comput. Vis. Image Underst. 80 (2000) 42–56.
[132] Y.S. Soh, H. Lee, Y. Wang, Invariant color model-based shadow removal in traffic image and a new metric for evaluating the performance of shadow removal methods, Pacific Rim International Conference on Artificial Intelligence (2006) 544–552.
[133] O. Javed, M. Shah, Tracking and object classification for automated surveillance, European Conference on Computer Vision (2002) 343–357.
[134] G. Daniel, F. Jan-Michael, K. Reinhard, A color similarity measure for robust shadow removal in real time, Proc. of Vision, Modeling, and Visualization, (2003), pp. 253–260.
[135] H.S. Choi, A New Shadow Removal Method in Color Traffic Image Sequence, Master's thesis Myongji University, 2004.
[136] P.B. Santosa, Evaluation of satellite image correction methods caused by differential terrain illumination, Forum Geografi 30 (1) (2016) 1–13.
[137] X. Shen, Q. Li, Y. Tian, L. Shen, An uneven illumination correction algorithm for optical remote sensing images covered with thin clouds, Remote Sens. 7 (9) (2015) 11848–11862.
[138] J.D. Shepherd, J.R. Dymond, Correcting satellite imagery for the variance of reflectance and illumination with topography, Int. J. Remote Sens. 24 (17) (2003) 3503–3514.
[139] P.L. Carmona, J.E. Moreno, F. Pla, C.B. Schaaf, Affine compensation of illumination in hyperspectral remote sensing images, Geoscience and Remote Sensing Symposium, 2009 IEEE International, IGARSS 2009 2 (2009) II–266.
[140] S.E. Franklin, P.T. Giles, Radiometric processing of aerial and satellite remote-sensing imagery, Comput. Geosci. 21 (3) (1995) 413–423.
[141] J. Wu, M.E. Bauer, D. Wang, S.M. Manson, A comparison of illumination geometry-based methods for topographic correction of QuickBird images of an undulant area, ISPRS J. Photogramm. Remote. Sens. 63 (2) (2008) 223–236.
[142] E. Grisan, A. Giani, E. Ceseracciu, A. Ruggeri, Model-based illumination correction in retinal images, 3rd IEEE International Symposium on Biomedical Imaging: Nano to Macro, 2006 (2006) 984–987.
[143] W.A. Mustafa, H. Yazid, S.B. Yaacob, Illumination correction of retinal images using superimpose low pass and Gaussian filtering, 2015 2nd International Conference on Biomedical Engineering (ICoBE) (2015) 1–4.
[144] B. Savelli, A. Bria, A. Galdran, C. Marrocco, M. Molinara, A. Campilho, F. Tortorella, Illumination correction by dehazing for retinal vessel segmentation, 2017 IEEE 30th International Symposium on Computer-Based Medical Systems (CBMS) (2017) 219–224.
[145] C. Leahy, A. O'Brien, C. Dainty, Illumination correction of retinal images using Laplace interpolation, Appl. Opt. 51 (35) (2012) 8383–8389.
[146] L. Kubecka, J. Jan, R. Kolar, Retrospective illumination correction of retinal images, J. Biomed. Imaging 2010 (2010) 11.
[147] R. Kolar, J. Odstrcilik, J. Jan, V. Harabis, Illumination correction and contrast equalization in colour fundus images, Signal Processing Conference, 2011 19th European (2011) 298–302.
[148] S.K. Saha, D. Xiao, Y. Kanagasingam, A novel method for correcting non-uniform/poor illumination of color fundus photographs, J. Digit. Imaging 31 (4) (2018) 553–561.
[149] H. Jelinek, M.J. Cree, Automated Image Detection of Retinal Pathology, Crc Press, 2009.
[150] G.D. Joshi, J. Sivaswamy, Colour retinal image enhancement based on domain knowledge, ICVGIP'08. Sixth Indian Conference on Computer Vision, Graphics & Image Processing, 2008 (2008) 591–598.
[151] F.W. Leong, M. Brady, J.O.D. McGee, Correction of uneven illumination (vignetting) in digital microscopy images, J. Clin. Pathol. 56 (8) (2003) 619–621.
[152] F. Piccinini, A. Bevilacqua, ColourVignetting correction for microscopy image mosaics used for quantitative analyses, Biomed Res. Int. 2018 (2018).
[153] G. Babaloukas, N. Tentolouris, S. Liatis, A. Sklavounou, D. Perrea, Evaluation of three methods for retrospective correction of vignetting on medical microscopy images utilizing two open source software tools, J. Microsc. 244 (3) (2011) 320–324.
[154] T. Peng, L. Wang, C. Bayer, S. Conjeti, M. Baust, N. Navab, Shading correction for whole slide image using low rank and sparse decomposition, International Conference on Medical Image Computing and Computer-Assisted Intervention (2014) 33–40.
[155] O. Chernavskaia, S. Guo, T. Meyer, N. Vogler, D. Akimov, S. Heuke, J. Popp, Correction of mosaicking artefacts in multimodal images caused by uneven illumination, J. Chemom. 31 (6) (2017) e2908.
[156] X.F. Mei, F.Y. Xie, Z.G. Jiang, Uneven illumination removal based on fully convolutional network for dermoscopy images, 2016 13th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP) (2016) 243–247.
[157] S. Singh, M.A. Bray, T.R. Jones, A.E. Carpenter, Pipeline for illumination correction of images for high-throughput microscopy, J. Microsc. 256 (3) (2014) 231–236.
[158] N. Dey, A. Ashour, S. Beagum, D. Pistola, M. Gospodinov, E. Gospodinova, J. Tavares, Parameter optimization for local polynomial approximation based intersection confidence interval filter using genetic algorithm: an application for brain MRI image de-noising, J. Imaging 1 (1) (2015) 60–84.
[159] N.S.M. Raja, S.L. Fernandes, N. Dey, S.C. Satapathy, V. Rajinikanth, Contrast enhanced medical MRI evaluation using Tsallis entropy and region growing segmentation, J. Ambient Intell. Humaniz. Comput. (2018) 1–12.
[160] A.E. Hassanien, N. Dey, S. Borra (Eds.), Medical Big Data and Internet of Medical Things: Advances, Challenges and Applications, CRC Press, 2018.
[161] N. Dey, A.S. Ashour, F. Shi, V.E. Balas, Soft Computing Based Medical Image Analysis, Academic Press, 2018.
[162] J. Juntu, J. Sijbers, D. Van Dyck, J. Gielen, Bias field correction for MRI images, Computer Recognition Systems, Springer, Berlin, Heidelberg, 2005, pp. 543–551.
[163] F.H. Lin, Y.J. Chen, J.W. Belliveau, L.L. Wald, Removing signal intensity inhomogeneity from surface coil MRI using discrete wavelet transform and wavelet

packet, Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2001 3 (2001) 2793–2796.
[164] L. Axel, J. Constantini, J. Listerud, Intensity correction in surface coil MR imaging, Am. J. Roentgenol. 148 (2) (1987) 418–420.
[165] W.M. Wells, W.E.L. Grimson, R. Kikinis, F.A. Jolesz, Statistical intensity correction and segmentation of MRI data, Visualization in Biomedical Computing 1994 2359 (1994) 13–25.
[166] M. Styner, C. Brechbuhler, G. Szckely, G. Gerig, Parametric estimate of intensity inhomogeneities applied to MRI, IEEE Trans. Med. Imaging 19 (3) (2000) 153–165.
[167] P.A. Narayana, A. Borthakur, Effect of radio frequency inhomogeneity correction on the reproducibility of intracranial volumes using MR image data, Magn. Reson. Med. 33 (3) (1995) 396–400.
[168] L.L. Wald, L. Carvajal, S.E. Moyher, et al., Phased array detectors and an automated intensity-correction algorithm for high-resolution MR imaging of the human brain, Magn. Reson. Med. 34 (3) (1995) 433–439.
[169] J.W. Murakami, C.E. Hayes, E. Weinberger, Intensity correction of phased-array surface coil images, Magn. Reson. Med. 35 (4) (1996) 585–590.
[170] B.H. Brinkmann, A. Manduca, R.A. Robb, Optimized homomorphicunsharp masking for MR grayscale inhomogeneity correction, IEEE Trans. Med. Imaging 17 (2) (1998) 161–171.
[171] W. Zhang, G. Li, Z. Ying, A new underwater image enhancing method via color correction and illumination adjustment, Visual Communications and Image Processing (VCIP), 2017 IEEE (2017) 1–4.
[172] J. Hoth, W. Kowalczyk, Colour correction of underwater images, OCEANS 2015-Genova (2015) 1–5.
[173] S.S. Sankpal, S.S. Deshpande, Nonuniform illumination correction algorithm for underwater images using maximum likelihood estimation method, J. Eng. 2016 (2016).
[174] C.Y. Li, J.C. Guo, R.M. Cong, Y.W. Pang, B. Wang, Underwater image enhancement by dehazing with minimum information loss and histogram distribution prior, IEEE Trans. Image Process. 25 (12) (2016) 5664–5677.
[175] J.Y. Chiang, Y.C. Chen, Underwater image enhancement by wavelength compensation and dehazing, IEEE Trans. Image Process. 21 (4) (2012) 1756.
[176] Y. Hu, K. Wang, X. Zhao, H. Wang, Y. Li, Underwater image restoration based on convolutional neural network, Asian Conference on Machine Learning (2018) 296–311.
[177] F. Zeng, S. Liu, K. Xiao, Adaptive uneven illumination correction method of document images, J. Comput. Methods Sci. Eng. 17 (3) (2017) 533–544.
[178] G. Meng, S. Xiang, N. Zheng, C. Pan, Nonparametric illumination correction for scanned document images via convex hulls, Age 9 (10) (2013) 11.
[179] B. Uhl, Day/night aerial surveillance system for fishery patrol, Airborne Reconnaissance XV vol. 1538, (1991) 140–148.
[180] B. Engler, S. Weddell, R. Clare, A digital prism wavefront sensor for ground-based astronomical image correction, 2018 International Conference on Image and Vision Computing New Zealand (IVCNZ) (2018) 1–6.
[181] S.S. Mostafa, L.N. Sousa, N.F. Ferreira, R.M. Sousa, J. Santos, F. Morgado-Dias, M. Wany, On the implementation of the gamma function for image correction on an endoscopic camera, 2016 3rd International Conference on Electronic Design (ICED) (2016) 470–475.
[182] M.R. Bales, Illumination Compensation in Video Surveillance Analysis, Doctoral dissertation Georgia Institute of Technology, 2011.
[183] D.N. Le, G.N. Nguyen, L. Van Chung, N. Dey, MMAS algorithm for features selection using 1D-DWT for video-based face recognition in the online video contextual advertisement user-oriented system, J. Glob. Inf. Manage. (JGIM) 25 (4) (2017) 103–124.
[184] N. Dey, A.S. Ashour, A.E. Hassanien, Feature detectors and descriptors generations with numerous images and video applications: a recap, Feature Detectors and Motion Detection in Video Processing, IGI Global, 2017, pp. 36–65.
[185] S. Goswami, U. Dey, P. Roy, A. Ashour, N. Dey, Medical video processing: concept and applications, Feature Detectors and Motion Detection in Video Processing, IGI Global, 2017, pp. 1–17.
[186] N. Dey, N. Dey, A. Ashour, S. Acharjee, Applied Video Processing in Surveillance and Monitoring Systems, IGI Global, 2016.
[187] Peli, Contrast in complex images, J. Opt. Soc. Am. A Opt. Image Sci. Vis. 7 (10) (1990) 2032–2032.
[188] Z. Ye, H. Mohamadian, Y. Ye, Discrete entropy and relative entropy study on nonlinear clustering of underwater and arial images, Proc. IEEE Int. Conf. Control Appl. (2007), pp. 318–323.
[189] S. Wang, J. Zheng, H.M. Hu, Naturalness preserved enhancement algorithm for non-uniform illumination images, IEEE Trans. Image Process. 22 (9) (2013) 3538–3548.
[190] T. Araki, N. Ikeda, F. Molinari, N. Dey, S. Acharjee, L. Saba, J.S. Suri, Link between automated coronary calcium volumes from intravascular ultrasound to automated carotid IMT from B-mode ultrasound in coronary artery disease population, Int. Angiol. 33 (4) (2014) 392–403.
[191] R. Thanki, S. Borra, N. Dey, A.S. Ashour, Medical imaging and its objective quality assessment: an introduction, Classification in BioApps, Springer, Cham, 2018, pp. 3–32.
[192] N. Ikeda, T. Araki, N. Dey, S. Bose, S. Shafique, A. El-Baz, J.S. Suri, Automated and accurate carotid bulb detection, its verification and validation in low quality frozen frames and motion video, IntAngiol 33 (6) (2014) 573–589.
[193] S. Borra, H. Lakshmi, N. Dey, A. Ashour, F. Shi, Digital image watermarking tools: state-of-the-art, Front. Artif. Intell. Appl. 296 (2017) 450–459.
[194] P. Mohammadi, A. Ebrahimi-Moghadam, S. Shirani, Subjective and objective quality assessment of image: a survey, arXiv preprint arXiv:1406.7799 (2014).
[195] S. Sangeetha, D. Vijay, An adaptive approach for image enhancement and naturalness preservation, Int. J. Recent Innov. Trends Comput. Commun 3 (10) (2015) 6033–6038.
[196] P.J. Bex, W. Makou, Spatial frequency, phase, and the contrast of natural images, J. Opt. Soc. Am. 19 (6) (2002) 1096–1106.
[197] D.G. Pelli, B. Farell, Why use noise? J. Opt. Soc. Am. A 16 (1999) 647–653.
[198] D.G. Pelli, P. Bex, Measuring contrast sensitivity, Vision Res. 90 (2013) 10–14.
[199] Z. Ye, H. Mohamadian, Y. Ye, Discrete entropy and relative entropy study on nonlinear clustering of underwater and arial images, IEEE International Conference on Control Applications, 2007. CCA 2007 (2007) 313–318.
[200] S. Sangeetha, D. Vijay, An adaptive approach for image enhancement and naturalness preservation, Int. J. Recent. Innov. Trends Comput. Commun. 3 (10) (2015) 6033–6038.