Morphological Background Detection and Images Enhancement with Object Recognition

Mr. Aniket V. Bhoyar
Asst. Professor, Deparment of Compuer Engineeirng.
Suresh Deshmukh College of Engineering, Wardha (M.S)
Email ID: aniket_bhoyar@rediffmail.com

Abstract:- In this paper, we have proposed two techniques i.e. image enhancement and object recognition which enhance the image in poor light for image processing application. The enhancement of images with poor contrast and detection of background. Proposes a frame work which is used to detect the background in images characterized by poor contrast and some morphological transformations are also used. The complete image processing is done using MATLAB simulation model. Some morphological transformations are used to detect the background in images characterized by poor lighting. The performance of the proposed operators is illustrated through the processing of images with different backgrounds, the majority of them with poor lighting conditions. Object segmentation can be accomplished by building a representation of the background scene named as background model and then detecting the changes in each new frame from the model. Any significant change in an image region from the estimated background model signifies a moving object. The performance of the proposed algorithm is illustrated and verified through the processing of different ideal synthetic and camera collected images, with backgrounds characterized by poor lighting conditions.

Keywords- *Image background, morphological contrast, morphological filters by reconstruction, multibackground.*

*****

1. Introduction

The increasing development of a digital image capturing devices, such as mobile phones, digital cameras and PDAs, their resolution is almost high enough to replace flatbed scanners. As a result, optical character recognition (OCR) technique and content-based image investigation techniques are receiving intensive attentions in recent years and text-mining tools are becoming essential [1]. Rather than all the contents in images, text information has stimulated great interests because of its high understandability by both human and machine, and wide applications, such as license plate reading, sign detection and translation, mobile text recognition, content-based web image search, object recognition, human computer interaction and so on [2], [3], [4]. In most cases, there is no assurance to keep the background in ideal condition during image capturing. In [5], an integrated image text information extraction system called TIE was described, but the system will be affected by noise pollution and uneven illumination [6], which is critical and not possible. Thus, de-noising and illumination normalization are necessary in order to get higher performance. Therefore we proposed, while non-uniform illumination is still a challenge in the field of text image recognition.

One of the most common techniques in normalization illumination image processing is histogram equalization and histogram specification, which are based on data statistical analysis, including global and local methods. However, there are some disadvantages for the two methods. For the main disadvantage of the global method, the global properties of the image cannot be properly applied in a local context the local method, it is easy to abate the image layers . Then, based on the assumption that lighting modes of the image are known or can be estimated, Shan proposed a normalization method called quotient illumination relighting But in reality, it is difficult to get prior knowledge of an image, and it is impossible for an prior knowledge to be applied to all images. A method called homomorphic filter performs well in image detail enhancement. However, as it works in the frequency domain, it takes a lot of effort in the transformation between time domain and frequency domain, yet considering poor local context. Another algorithm, proposed by Jimenez-Sanchez, divides image to blocks and takes the average of the max and minimal values of each blocks as the background of the corresponding areas A local spatial co-occurrence based background modeling approach was presented to automatically estimate the local context background, but only worked well on human tracking. This algorithm is simple and being widely used. However, due to the use of single structuring element, it cannot acquire good

processing results under complex lighting conditions, and this method will result in blocking effect as well. Therefore, even though the reported algorithms to compensate changes in lighting varied, some are more adequate than others.

In this work, a morphological methodology to compute the image illumination background is proposed. Due to the nice characteristics of opening by reconstruction, which introduces almost no shape noise in both filtering and detection of structures , we replace the opening operation with it to develop the classical Top-Hat transform and further avoid blocking effect. Afterwards, modified Top-Hat operations with multi direction structuring elements (M-SEs) are applied to extract image information with different texture directions, components of which are fused to get a complete equalization illumination image.

The proposals given in this paper are illustrated with several examples. The proposed method and some other reported methods are compared, under the ideal synthetic images with four different lighting modes and captured images with noise characterized by 3 different languages texture.

2. Morphological Transforms

Mathematical morphology (MM), specifically a collection of operators, is based on set theory and defined on an conceptual structure. The conceptual structure is an infinite lattice, which was first systematically examined by Matheron and Serra in the 1960s and is an extension of Minkowski's set theory . For MM technology, its purpose is to analyze the shape and structures of the concerned target. Due to the powerful image analysis and image enhancement capabilities with morphological transformation, including corrosion, dilation, opening, closing, rank filters (including median filters), Top-Hat transforms, and other derived transforms, MM is widely used in the field of image processing. MM involves structuring element set and image set.

2.1 Basis of MM transforms

MM involves image set and structuring element set (SE).

The result of erosion operation to an image shows where the SE fits the objects in the image. In gray scale, eroding an image f by SE B is defined as follows: $[\varepsilon_B(f)](x) = \bigwedge_{b \in B} f(x+b)$ ……(1)

The result of dilation operation to an image shows where the SE hits the objects in the image. The dilation is expressed as follows: $[\delta_B(f)](x) = \bigvee_{b \in B} f(x+b)$ …….(2)

Opening (closing) is the sequential combination of erosion (dilation) and dilation (erosion) with SE and its reflection. The idea behind opening is to dilate an eroded image in order to recover the eroded image as much as possible. In contrast, the closing is to recover the dilated image. $\gamma_B(f) = \delta_{\check{B}}[\varepsilon_B(f)]$ …..(3) $\phi_B(f) = \varepsilon_{\check{B}}[\delta_B(f)]$ …….(4)

2.2 Opening and Closing as a result of Reconstruction

Very firstly compare with opening and closing transforms, opening and closing by reconstruction are concepts that are more useful. They allow the elimination of undesirable region without considerably affecting the remaining structures of the image, and will be helpful for recovering structures which are not completely destroyed by erosion or dilation. The characteristic arises from the way the transformation is built by means of geodesic dilation and corrosion transform.

Geodesic dilation and erosion involve two images: mark image f and mask image g. Mark image is the image to be processed; mask image plays a limited role in the spread of mark image's expansion.

Geodesic dilation and erosion of mark image relative to mask image are expressed as follows of one size scale, respectively $\delta_g^{(l)}(f) = \delta^{(l)}(f) \wedge g$ (5)
$\varepsilon_g^{(l)}(f) = \varepsilon^{(l)}(f) \vee g$ (6)

Here, $\wedge$ means taking minimum value point by point, and $\vee$ means taking maximum value point by point.

Geodesic dilation and erosion are dual operations.

$$\varepsilon_g^{(l)}(f) = [\delta^{(l)}(f^c) \wedge g^c]^c = [(\varepsilon^{(l)}(f))^c \wedge g^c]^c = [\varepsilon^{(l)}(f) \vee g$$

Of size i, geodesic dilation and erosion of mark image f relative to mask image g can be realized by iteration as: $\delta_g^{(i)}(f) = \delta_g^{(l)}[\delta_g^{(i-1)}(f)]$ (7) $\varepsilon_g^{(i)}(f) = \varepsilon_g^{(l)}[\varepsilon_g^{(i-1)}(f)]$ (8)

Conceptually this may continue indefinitely, but for all practical purposes iteration is terminated at an integer n such that no change would occur after that.

The stable output termed as reconstruction by dilation and erosion is denoted by $R_g^{\delta}(f)] = \delta_g^{(n)}(f)$ (9) $R_g^{\varepsilon}(f)] = \varepsilon_g^{(n)}(f)$ (10)

Here, n represents the iteration number, and reconstruction by geodesic dilation and erosion are dual operations

When the mark image f is equal to the erosion of the mask image g, we will obtain the opening and closing by reconstruction as follow, as shown in Fig. 1 and Fig. 2.

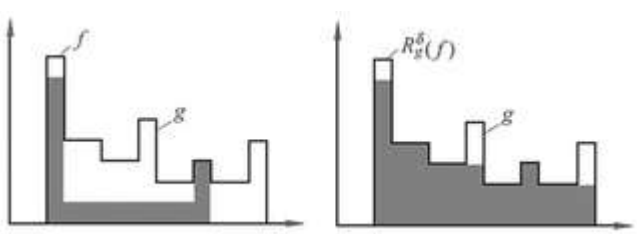

Figure 1. Illustrates reconstruction by opening of mark image f relative to mask image g.

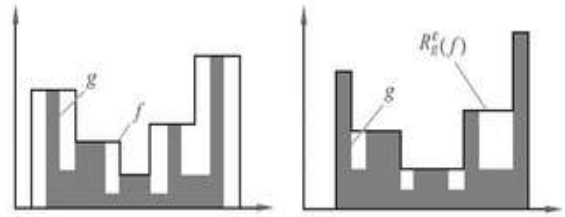

Figure 2. Illustrates reconstruction by closing of mark image f relative to mask image g.

$$\tilde{\gamma}_R(g) = \gamma_R^{(n)}(g) = R_g^{\delta}[\varepsilon^{(n)}(g)] \quad (11)$$

$$\tilde{\phi}_R(g) = \phi_R^{(n)}(g) = R_g^{\varepsilon}[\delta^{(n)}(g)] \quad (12)$$

3. Opening by the Reconstruction with the Modified Top-Hat Transform.

3.1 Classical Top-Hat transform.

Usually, opening and closing operations are used in morphological filters to smooth the image. Opening an image will smooth the contour, reduce small islands and sharp peaks or capes, while closing an image will smooth the contour.

The proper morphological filter selection of depends on the previous knowledge of target's sharp, size and direction. Opening and closing operations with SE will eliminate the structures unmatched with SE in image. These structures can be restored through difference operation between original image and its opening or closing results. Thus we proposed based on the difference operation, morphological transformations called WTH (white Top-Hat) and BTH (black Top-Hat)

The WTH transformation obtains all bright features and sub graphs that are unable to accommodate SE: $g^w(f) = f - \gamma_B(f)$ (13)

BTH is the dual operation of WTH, which sieves out the dark features and sub-graphs smaller than SE: $[g^b(f^c)]^c$

$$= t_{max} - g^{\omega}(t_{max} - f)$$

$$= t_{max} - t_{max} + f + \gamma_B(t_{max} - f)$$

$$= t_{max} + f - \phi_B(f)$$

In text information images, information is represented by the strength of revolution in image. The change of image in sequence is more extreme and intensive than that of irregular illumination background, which means that the connected regions of image is much smaller than that of the illumination background in poor light.

Since opening operation can remove image features slighter than size of structural element SE, image area smaller than SE size will withdraw after the opening function transformation, and connected regions bigger than the SE will be saved. Therefore, all skin texture will be eliminated with intensity function retain if large scale SEs is used on image for opening operation.

Thus, the use of Top-Hat transform would output a uniform brightness image.

On the other hand, from the perspective of frequency domain filtering, Top-Hat change works as a high-pass filter. Since the image information locates in the high frequency domain with brightness gradient locating in the low regularity domain, the Top-Hat convert can be used for image light equalization.

As shown in Fig. 3 and Fig. 4, an uneven illumination text image and result of Top-Hat transform is represented.

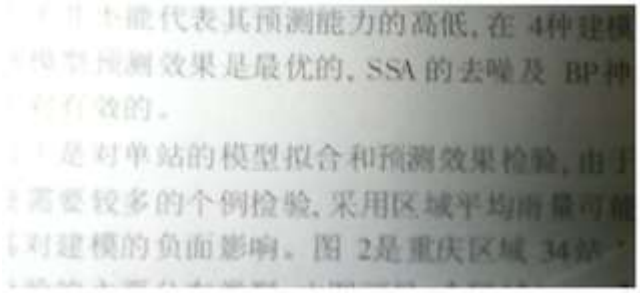

Figure 3. Uneven illumination text image.

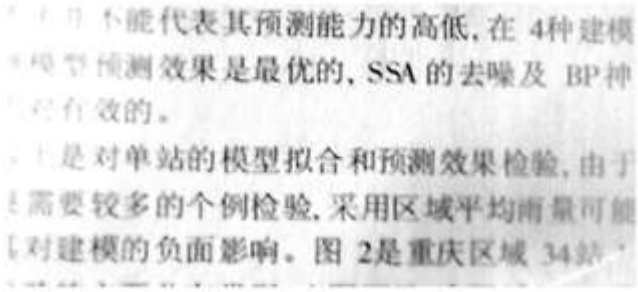

Figure 4. Result of Top-Hat transform with block effect.

Though, since the opening operation will generate new fake contours when the structuring element is enlarged, mutation at the edge of SE on extracted background brightness without a perfect preservation of the edge information will occur. Therefore, edge noise will be introduced with opening based Top-Hat transform, and results in block effect. As shown in and which mean the illumination normalized result and the extracted uneven background with block effect. In order to clearly show the block effect, image gray-scale of is adjusted to a larger range, as shown in And some other images with obvious block effect are shown in Section 5.

Figure 5. (a)–(b) Uneven background with block effect.

3.2 Modified Top-Hat transform

The key drawback of conventional opening and closing is that they do not allow a wonderful preservation of the edge information and will introduce fake contours .However, it is possible to design morphological filters by reconstruction that convince the above requirement of preserving edge information and introducing no fake contours, and at the same time consider both shape and size features. Morphological opening by reconstruction is such a filter. Compared with other morphology operations, opening by reconstruction can maintain patterns that were not removed completely by erosion. Fig. 6 shows the difference between conventional opening and opening by reconstruction.

Figure 6. (a) Original image, (b) result of conventional opening of (a) using a disk SE, and (c) result of opening by reconstruction of (a) with same SE.

Through RWTH transform, which is based on opening by reconstruction to equalize illumination, result shows balanced changes in the illumination background and no blocking effect, as shown in Unfortunately, here arises another seemingly more serious problem, that part of the

text information is mistaken as background illumination due to over-illumination equalization. Opening by reconstruction will reconstruct edge information of the features, leading to the spread of edge and part of the foreground image information being removed by RWTH transformation as background illumination.

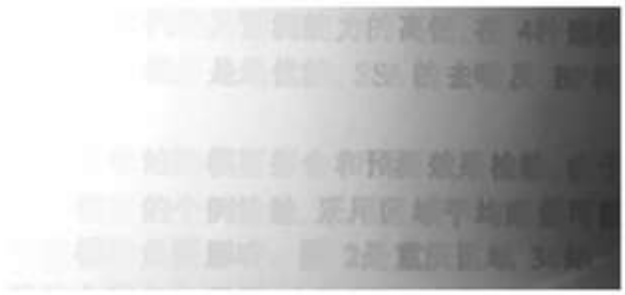

Figure 7. Background without block effect but with over illuminated.

In order to correct the over-illumination equalization phenomenon, closing by reconstruction, which is the dual operation of opening by reconstruction, is utilized to eliminate valid information mistaken as illumination background, and get real background estimation. The real background estimation is expressed as follows. $\phi_{\gamma}(f)=\tilde{\phi}_R[\tilde{\gamma}_R(f)]$ (16)

Thus, the real modified Top-Hat transform is obtained by replacing Eaq.15. In the following discussion, unless otherwise mentioned, "Top-Hat transform" refers to "the real modified Top-Hat transform", which is represented as follows. $\tilde{g}(f)=f-\phi_{\gamma}(f)=f-\tilde{\phi}_R[\tilde{\gamma}_R(f)]$ (17)

When these operators, i.e., sequential combination of closing by reconstruction and opening by reconstruction, are used, the problems above, such as blocking effect and over-illumination equalization, can be solved.

The obtained illumination background is shown in Fig. 8(a). Fig. 8(a) is also adjusted in the same way as Fig. 5(a), and the adjusted image shown in Fig. 8(b) shows that the block effect is avoided effectually.

Figure 8. (a)–(b) Background without any block effect or over illumination.

4. The Multi Direction SEs Based Illumination Equalization Algorithm

4.1 Multi-direction SEs based top-hat transforms

The elements are sensitive to the image which has the same direction with SE, and thus edges with different directions from the SE will be smoothed. Therefore, using single SE to do background estimation cannot remain good image details, and will cause a big deal of background leakage especially when uneven lighting degree is large and image background is of strong fluctuation. When signal noise ratio is low, from the above analysis, it is obvious that Multi-direction SEs based top-hat transforms have more advantages over single structuring morphological transform. So we use big scale Multi-direction SEs to implement Top-Hat transform.

In this paper, based on Multi-direction SEs, uneven illumination background correction algorithm is proposed, and linear SEs with different directions 0°, 45°, 90° and 135° are selected, scales of which are 1/4 of the smallest scale of image row and column, as shown in Fig. 9.

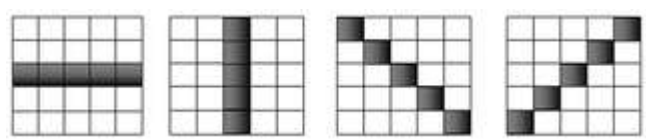

Figure 9. Different SEs used in proposed algorithm.

4.2 Introduction to information entropy

Shannon proposed entropy in 1948, which is mainly used to measure the abundance degree of information. For single image, gray value of each pixel can be considered as independent, and entropy is defined as the amount of information contained in image, mathematically given as:

$$H=-k\sum_{i=0}^{L-1}p_i log_2 p_i \quad (18)$$

Here, L is the total number of grey levels, and $p=\{p_0,p_1,\cdots,p_{L-1}\}$ is the probability of occurrence of each level. Larger H indicates more information.

For an $M \times N$ gray image, $L = 256$, $k = 1/(M \times N)$, then entropy of the image is:

$$H = -1/(M \times N) \sum_{i=0}^{255} p_i log_2 p_i \quad (19)$$

4.3 The illumination normalization algorithm based on Multi-direction SEs top-hat transforms

Information contained in text image is intuitively represented by the insensitive change of image. The change of text information presented by image is drastic, while change in uneven illumination background is relatively flat. Meanwhile, sub-images are obtained by extracting features of different directions through multi-direction SEs Top-Hat transform. Their information content can be measured by information entropy. Therefore, information entropy can be used as weights, as shown in the following, to merge the sub-graph, and to get the final illumination equalization image.

$$\omega_i = H_i / \sum_{i=1}^{n} H_i \quad (20)$$

Here, H_i represents the entropy of image processed by Top-Hat transform with Multi-direction SEs, and ω_i represents the image's weight factor, n is the number of Multi-direction SEs.

From Equ.17 and Equ.20, we can get the final illumination equalization image, as shown in Equ.21.

$$f_{TH} = \sum_{i=1}^{n} \omega_i \tilde{g}_i(f) \quad (21)$$

The whole structuring diagram of the new algorithm based on multiple structures is illustrated in Fig. 10.

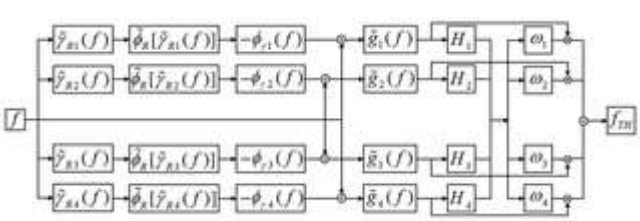

Figure 10. Diagram of the proposed algorithm.

Then, another simple relation is employed to get a better image as shown in Equ.22. $f = \wedge(\tilde{g}_i, f_{TH})$ (22)

Finally, a simple contrast enhancement technology is used and the final illumination normalized output of is shown in Fig. 11.

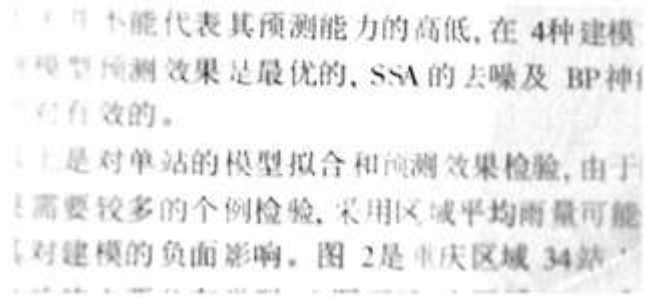

Figure 11. Final illumination normalized output without block effect or fake contours.

In conclusion, the proposed algorithm can be used for uneven illumination text images with poor lighting. Algorithm works well on removing uneven illumination background without introducing new contours noise, and it is not sensitive to noise, and is suitable for images captured by digital devices which have high noise.

Conclusions

This paper presents a study to detect the text image uneven illumination background and to normalize uneven illumination images with poor lighting. Firstly, a classical Top-Hat transform methodology, which would result in block effects and fake contour, was introduced to compute an approximation of the background. This transform was then redefined by replacing opening operation with opening by reconstruction, which is called RWTH transform. However, problem called over-illumination equalization was detected when the morphological opening by reconstruction was employed. Therefore, a dual operation called closing by reconstruction was introduced. Additionally, multi-direction structuring elements were used to modify the Top-Hat transform and balance the direction information.

The performance of the proposals was illustrated by several ideal examples with different uneven illumination modes, and some camera collected text images with Chinese, English and Japanese texture. In addition, the performance operators employed in this paper was compared with others given in the literature. Results show that the proposed algorithm is more advantageous over others in obtaining uniform

illumination images, retaining edge information and introducing no contour. However, our proposed algorithm requires large amount of computation and storage space because of the loop definition of morphological reconstruction. Further studies will be carried out to optimize this algorithm to reduce its computation work and storage space, and implement this algorithm through ASIC (application specification integrated circuit).

References

[1] Pafilis E, Frankild SP, Fanini L, Faulwetter S, Pavloudi C (2013) The SPECIES and ORGANISMS Resources for Fast and Accurate Identification of Taxonomic Names in Text. PLoS ONE vol.8 no.

[2] Jian Liang, David Doermann, Huiping Li (2005) Camera-based analysis of text and documents: A survey. International Journal of Document Analysis and Recognition vol.7 no.2

[3] Yao C, Zhang X, Bai X, Liu W, Ma Y (2013) Rotation-Invariant Features for Multi-Oriented Text Detection in Natural Images. PLoS ONE vol.8 no.

[4] Zhong B, Yao H, Chen S, Ji R, Chin TJ, et al. (2013) Visual Tracking via Weakly Supervised Learning from Multiple Imperfect Oracles. Elsevier Pattern Recognition vol.47 no.3

[5] Juang BH, Katagiri S (1992) Discriminative learning for minimum error classification [pattern recognition]. Signal Processing IEEE Transactions on vol.40

[6] Pan YF, Hou X, Liu CL (2011) A Hybrid Approach to Detect and Localize Texts in Natural Scene Images. Image Processing IEEE Transactions on vol.20, no.3

[7] Bibina VC, Viswasom S (2012) Adaptive wavelet thresholding & joint bilateral filtering for image denoising. in Proc. INDICON 1100–1104.

[8] KinTak U, He X, Yang B, Qi D, Tang Z (2010) A Novel Image Denoising Algorithm Based on Non-uniform Rectangular Partition and Interpolation. in Mediacom Hong Kong China 9–12. doi: 10.1109/mediacom.2010.

[9] Chen Y, Yang J, Shu H, Shi L, Wu J (2014) 2-D Impulse Noise Suppression by Recursive Gaussian Maximum Likelihood Estimation. PLoS ONE vol.9, no. 5.