

Face Enhancement With Variable Illumination And Noise

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Abstract— In order to improve the overall effect of face images with variable illumination, this paper implemented an effective face enhancement algorithm with variable illumination based on Retinex. Firstly, this algorithm divides the original image into the illuminant image and the reflectance image by using the bilateral filter, then different strategies are used to compress the illuminant image and to enhance the reflectance image. At last, it composes the two part images to a new image. The experimental results on several images show that the algorithm can prevent the "halos" phenomenon, and can restore the original face image, so the face image is more suitable for human eye observation.

Keywords—face enhancement; variable illumination; Retinex; bilateral filters; 2D convolution; fft2

I. INTRODUCTION

When people are missing one of his/her family members or friends who's already gone, they always look at their photos since this is the only way to remembering them and seeing their faces. Fortunately, we don't need to worry about the quality of the photos now since we have many advanced hardware and technique. However, some old photos may be taken under bad conditions. Variable illumination, noise always affect photos. The goal of this paper is to reduce the influence of illumination and noise in old photos and improve the overall effect of face images to make it more suitable for human eye observation.

II. IMAGE DENOISING

In fields such as image processing, computer vision, image denoising is a basic process and also an important research in digital image processing. According to the different characteristics of the image and the noise, researchers established a lot of image denoising algorithms. They are divided into two categories: denoising algorithm in spatial domain and denoising algorithms in frequency domain.

A. Histogram Equalization

Histogram equalization is a histogram correction method based on cumulative distribution function transformation method. In order to achieve the effect of image signal enhancement, it transforms an image with given gray

probability distribution into a new image with a balanced probability distribution.

For convenience, we take the r , s denotes the gray scale level of the original image and the image after histogram equalization, respectively, namely $0 \leq r, s \leq 1$. Assume there is a monotone increasing transform $S = T(r)$ in $[0, 1]$ and $0 \leq T(r) \leq 1$, and its inverse transform $r = T^{-1}(S)$. According to the probability theory, given the probability density $P_r(r)$ of a random variable r , another random variable s is a function of r . The probability density of $P_s(s)$ of s can be calculated:

$$P_s = \frac{d}{ds} \left[\int_{-\infty}^r P_r(r) dr \right] = P_r(r) \frac{dr}{ds} = P_r(r) \frac{d}{ds} [T^{-1}(S)] \quad (1)$$

From equation (9) we can see, the probability density can be controlled by $T(r)$. That's the essential idea of histogram equalization.

According to the regulation of normalization:

$$P_s(s) = 1 \quad (2)$$
$$ds = P_r(r) dr$$

Integrate on both sides:

$$S = T(r) = \int_0^r P_r(r) dr \quad (3)$$

Equation (11) is the transform function we want. When it says is when the transform function $T(r)$ is the histogram cumulative distribution function of the original image, we can achieve histogram equalization.

Its discrete form:

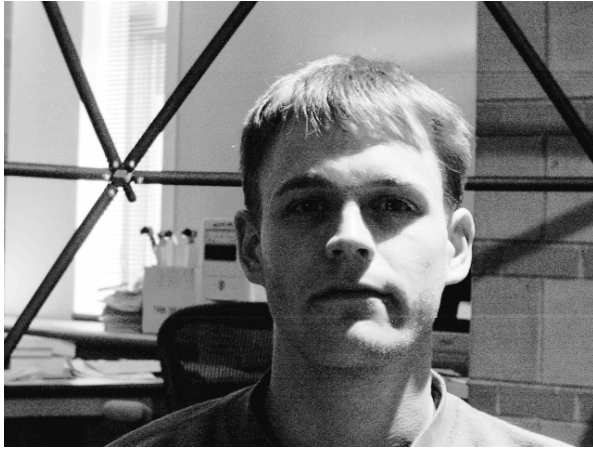
$$s_k = T(r_k) = \sum_{i=0}^k P_i(r_i) = \sum_{i=0}^k \frac{n_i}{n} \quad (4)$$

As we can see, the gray scale of each pixel s_k after equalization can be calculated by the histogram of the original image directly.

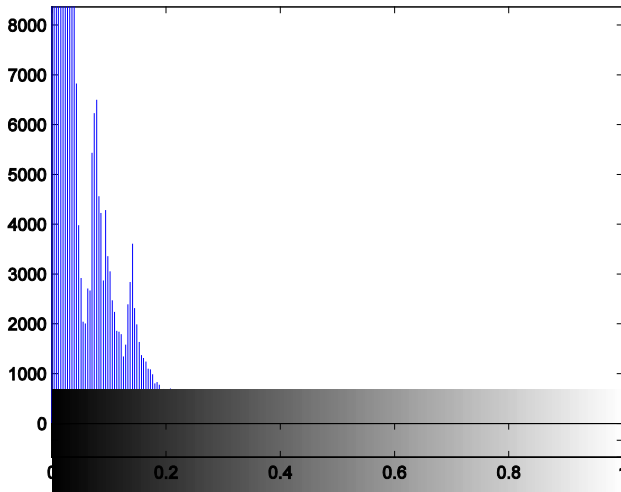


Original Image

(a)



(b)



(c)

Fig. 1. (a) The Original Image
(b) The Enhanced Image After Histogram Equalization
(c) The Histogram of the Original Image

B. Bilateral Filters

Bilateral filter is a kind of anisotropic filtering algorithm. It is able to protect the edge information in filtering through image intensity transformation. According to the special relationship and the value relationship of pixels, bilateral filtering can be defined as following:

$$h[I_p] = c \sum_{q \in I_p} G_{\sigma_d}(\|p - q\|^2) G_{\sigma_r}(g_p - g_q) g_p \quad (5)$$

In this equation, c is the normalization constant, I_p is the image centered on p , g_q g_p is the pixel value on q and p respectively.

G_{σ_r} is a function of difference of pixel gray level $\delta(g_p, g_q)$:

$$G_{\sigma_r}(x) = \exp\left\{-\frac{\delta(g_p, g_q)^2}{2\sigma_r^2}\right\} \quad (6)$$

G_{σ_d} is a function of the Euclidean distance $d(p, q)$:

$$G_{\sigma_d}(x) = \exp\left\{-\frac{d(p, q)^2}{2\sigma_d^2}\right\} \quad (7)$$

In bilateral filtering, the standard deviations of two Gaussian function σ_r and σ_d determines its performance.

III. VARIABLE ILLUMINATION

Eliminating variable illumination is complex and important in face enhancement. In this section we talk about the Retinex algorithm and its deficiencies.

A. The Basic Retinex Algorithm

Retinex is a commonly used image enhancement method based on scientific experiments and scientific analysis. Like Matlab, which is synthesized from Matrix and Laboratory, Retinex is synthesized from retina and cortex. When Edwin H.L first proposed this algorithm in 1963, he made three assumptions. First, there's no color in real word. Our perception of color is just the result of the interaction of light and matter. For example, we saw the water is colorless, but the water film and soap film is colorful, which is the result of thin film light interference. Secondly, each color area is formed by

three primary colors with fixed wavelength, which is red, green, and blue. Thirdly, the three primary colors determine the color of each unit area.

The basis of Retinex theory is the color of the object is decided by the light reflection ability of the objects reflect long wave (red), medium wave (green), and short wave (blue), rather than the absolute value of the intensity of the reflected light. The color of the object is not affected by light heterogeneity. The color is consistently, namely Retinex is based on the color constancy. Different from the traditional linear and non-linear methods which can only enhance one kind of characteristics of an image, Retinex can balanced an image in three aspects, dynamic range compression, edge enhancement, color constancy, thus can be used to enhance different types of image adaptively.

According to Retinex theory, an image may be regarded as the product of the illumination image and the reflect image. As shown in the following type:

$$S(x, y) = R(x, y) \times L(x, y) \quad (8)$$

S for the original image, R for the reflected image, L for the illumination image. In fact, the reflected image R really determines the essential property of an image. The illumination image L determines the dynamic range that an image can achieve. The purpose of Retinex is to get the essential property of an image from the original image S to avoid the influence of illumination and achieve the color constancy.

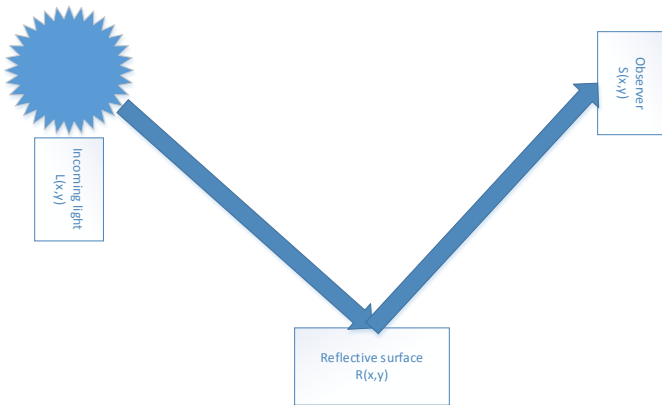


Fig. 2. Retinex Algorithm

In the actual calculation of Retinex, people always use the logarithmic transformation first to transform the relationship of product into the relationship of sum, then implement the image decomposition. The specific way is to first take logarithm of the original image, and then use specific method to estimate the intensity of illumination to get L, the illumination image. Following the fact when estimating the illumination image: The illumination image is part of the original image signal with slow transformation. Then the reflected image is the difference between the original figure S and the illumination image. In the next step, different strategies are used to compress the illuminant image and to enhance the reflectance image. Finally, we synthesis the new image.

$$\text{Log}[S(x, y)] = \text{Log}[R(x, y)] + \text{Log}[L(x, y)] \quad (9)$$

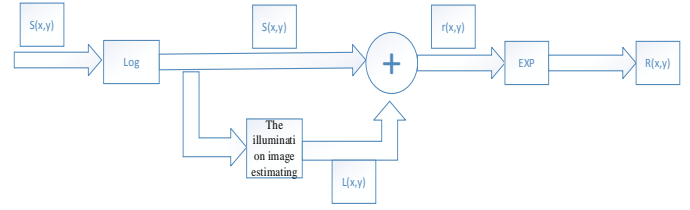


Fig. 3. The General Retinex Algorithm Flow Chart

B. Single Scale Retinex(SSR)

We usually estimates the illumination image as space smoothing image. In the Log-domain,

$$r(x, y) = \text{Log}[R(x, y)] = \text{Log}[S(x, y)] - \text{Log}[L(x, y)] \quad (10)$$

The SSR algorithm uses Gauss function $G(x, y)$ to estimate.

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (11)$$

$$\iint G(x, y) dx dy = 1 \quad (12)$$

So we get:

$$L(x, y) = S(x, y) \times G(x, y) \quad (13)$$

After SSR we get:

$$r(x, y) = \text{Log}[S(x, y)] - \text{Log}[S(x, y) * G(x, y)] \quad (14)$$

Finally, we have the enhanced image:

$$r(x, y) = \text{Log}[S_i(x, y)] - \text{Log}[S_i(x, y) * G(x, y)] \quad (15)$$

$F(x, y)$ is called rewind function. Usually, we let

$F(x, y) = G(x, y)$. $S_i(x, y)$ denotes the i_{th} color components.



Fig. 4. The Enhanced Image After SSR

C. Deficiencies of The Basic Retinex Algorithm

From Fig.3, we can see some enhancement of the face especially the dark part. But for some edge of the area with strong illumination change, the phenomenon of “halo” occurs. This is mainly due to the assumption of the single scale Retinex algorithm that the light within the entire image is smooth, which is very difficult to satisfy in natural environment.

Actually, decomposing an image into two images is a "sick" problem in mathematics. Because the brightness a single pixel express both the illumination information and the image content. In this case, we have to calculate the relationship between the pixel itself and other pixels in the image in order to estimate the intensity of illumination accurately. Existing technology in computing illumination mainly gives weight to nearby pixel according to the pixel location to estimate the current pixel intensity of illumination, which is lack of fully consideration of the meaning of the pixel brightness itself. This led to the influence of the pixels of high and low value at the edge of both sides when estimating the illumination of high contrast edges intensity of illumination: the high value of pixel intensity of illumination is affected by low values of pixels adjacent to estimation of the intensity of illumination is low; Low pixel intensity of illumination is estimated high because the influence of high values of pixels. This creates a region illumination estimated distortion and then “halo” appears in the image.

IV. RETINEX BY TWO BILATERAL FILTERS

It's never easy to estimate the illuminant since there are too many ways. In this paper, we try to use Retinex based on bilateral filters which is a useful filter that can reserve the image edges.

A. Why Bilateral Filters

The assumption that the illumination is uniform in the whole image leads to “halo”. Because in traditional Retinex algorithm, convolution kernel function only consider the influence of position to estimate of the pixel values. Without considering the differences between the nearby pixel values, the pixels on both sides affect our estimation. In order to consider the influence of pixel values on both sides of the border area, here we use the method bilateral filtering to estimate of the illumination image.

B. Results



(a)



(b)



(c)

Fig. 5. (a) The Original Image
 (b) The Illumination image
 (c) The Retinex Image Using Bilateral Filters

From the figures above we can get a positive result, using bilateral filters can eliminate the influence of illumination and avoid “halo”.

V. CONCLUSION AND APPLICATION

In my project, in order to improve the overall effect of face images, I used several methods to reduce the influence of noise and variable illumination.

Methods about denoising include histogram equalization, wave transform, stretching, average convolution, and deconvolution. (The last three methods are introduced in lecture or homework)

To eliminate the influence of variable illumination, I looked through Retinex, single scale Retinex and multi-scale Retinex and finally located on Retinex using bilateral filtering.

These methods may be mixed in actual face enhancement. They can restore the face image and make it more suitable for the human eye observation. People can remember their friends or family members in a better way. Besides, bilateral Retinex seems like a very good match for video purposes since there is no need to estimate motion.

REFERENCES

- [1] Elad, Michael, "Retinex by two bilateral filters." *Scale Space and PDE Methods in Computer Vision*. Springer Berlin Heidelberg, 2005. 217-229.
- [2] Blake A. Boundary conditions for lightness computation in Mondrian world[J]. *Computer Vision, Graphics, and Image Processing*, 1985, 32(3): 314-327.
- [3] Funt B, McCann J, Ciurea F. Retinex in MATLAB™[J]. *Journal of electronic imaging*, 2004, 13(1): 48-57.
- [4] Kimmel R, Elad M, Shaked D, et al. A variational framework for retinex[J]. *International Journal of computer vision*, 2003, 52(1): 7-23.
- [5] Elad M, Kimmel R, Shaked D, et al. Reduced complexity retinex algorithm via the variational approach[J]. *Journal of visual communication and image representation*, 2003, 14(4): 369-388.
- [6] Jobson D J, Rahman Z U, Woodell G A. Properties and performance of a center/surround retinex[J]. *Image Processing, IEEE Transactions on*, 1997, 6(3): 451-462.
- [7] Tomasi C, Manduchi R. Bilateral filtering for gray and color images[C]//*Computer Vision*, 1998. Sixth International Conference on. IEEE, 1998: 839-846.
- [8] Boyle, Richard, Milan Sonka, and Vaclav Hlavac, *Image Processing, Analysis, and Machine Vision*, First Edition, University Press, Cambridge, 1993.