Automatic retinal image quality assessment and enhancement

Lee, Samuel, Wang, Yiming

Samuel C. Lee, Yiming Wang, "Automatic retinal image quality assessment and enhancement," Proc. SPIE 3661, Medical Imaging 1999: Image Processing, (21 May 1999); doi: 10.1117/12.348562

SPIE.

Event: Medical Imaging '99, 1999, San Diego, CA, United States

Automatic retinal image quality assessment and enhancement

Samuel C. Lee* ,Yiming Wang

School of Electrical and Computer Engineering, Univ. of Oklahoma, Norman, OK 73019

ABSTRACT

This paper describes a method for machine (computer) assessment of the quality of a retinal image. The method provides an over-all quantitative and objective measure using a quality index Q. The Q of a retinal image is calculated by the convolution of a template intensity histogram obtained from a set of typically good retinal images and the intensity histogram of the retinal image. After normalization, the Q has a maximum value of 1, indicating excellent quality, and a minimum value of 0, indicating bad quality. The paper also presents several application examples of Q in image enhancement. It is shown that the use of Q can help computer scientists evaluate the suitability and effectiveness of image enhancement methods, both quantitatively and objectively. It can further help computer scientists improve retinal image quality on a more scientific basis. Additionally, this machine image quality measure can also help physicians make medical diagnosis with more certainty and higher accuracy. Finally, it should be noted that although retinal images are used in this study, the methodology is applicable to the image quality assessment and enhancement of other types of medical images.

Keywords: Quality Assessment, Quality Measure, Template, Histogram

1. INTRODUTION

Image enhancement operations improve the quality of an image. They can be used to improve an image's contrast and brightness characteristics, reduce its noise content, or sharpen its details. However, what is considered an improvement in the image is often subjective and is generally dependent upon the application, as well as on the judgment of the observer. Image processing applications are intended to produce images that are to be viewed by either human observers or automated industrial inspection (machine vision system). Because of the not-well-understood human visual system, no objective measure exists for judging the quality of an image that corresponds to human assessment of image quality, and there is no so-called "typical" observer[1]. On the other hand, as opposed to human visual system, computer vision is a well-known system in terms of its capabilities in perception of an image sensitivities in brightness, color, frequency, and other statistics (such as average, standard deviation, pixel variation, and signal-to-noise ratio). Thus, based on machine assessment of image quality, a method for objective measure of image quality could be developed. Image quality measure is a very important subject in image processing in general and image enhancement, restoration, data compression, and object recognition in particular. Thus, there is a need for searching a method which can quantitatively measure and describe the over-all quality of an image for applications as such, whereby an automatic system can be established for testing and evaluating image quality and its improvement. In addition to fulfill the need above, the other major purpose of this paper is to show how the image quality index Q can be used in retinal image enhancement process.

2. METHOD AND DESIGN

2.1. Establishing A Computer Image Quality Measure Standard

In our recent development of a real-time diabetic retinopathy expert (DR. X) computer system[2-10], a set of 360 retinal images

* Correspondence: Email: samlee@mailhost.ecn.ou.edu; Telephone: 405 325 4289; Fax: 405 325 7066

obtained from the Oklahoma Indians (a population with a high risk of having diabetic retinopathy[11-12]) were examined by a retinal specialist and DR. X. It was concluded the quality of a color retinal image is predominantly by three essential image quality parameters: brightness, contrast, and signal-to-noise (*SNR*). From these 360 images, we selected a set of 20 images with excellent quality and use them as the "desired" retinal images or images with highest quality for establishing an image quality measure standard. From these desired images, we can subsequently obtain the "desired" values of the three essential image quality parameters, and the average intensity histogram, which will be referred to as the "desired" or template intensity histogram. We have also observed that the individual and combined effects of these three parameters can be measured in the intensity histogram. Conversely, when the brightness, contrast, and *SNR* values of a retinal image are close to their respective desired values, the intensity histogram of the image will also be close to the template intensity histogram. Therefore we propose a machine quality measure using the convolution of the template intensity histogram and the histogram of the image.

2.2. Template Intensity Histogram of Retinal Images for Quality Measure

One of the desired retinal images and its intensity histogram approximated as a Gaussian curve are shown in Figures 1a and 1b. The range of the retinal band R is defined to be the range where the total number of pixels are 99% of the total retinal pixels, with $T_2 - M = M - T_1$, that is, $R = T_2 - T_1$. Based on our studies, contrast of retinal images can be measured using R, knowing that the R is linearly proportional to retinal image contrast. The greater the value R, the higher the image contrast. With the knowledge of the desired mean value and the range of retinal band, a template (intensity) histogram of retinal images can be constructed and mathematically approximated by

$$f(i) = A * \exp(-(i - M)^2 / 2\sigma^2) \tag{1}$$

where i (from 0 - 255) is the pixel intensity (gray-level), A is the peak value of the Guassian curve, M is the desired mean value of the over-all pixel intensity, and σ is the standard deviation, which, according to the Gaussian distribution, is about one sixth of the range of the retinal band R (Fig. 2), that is.

$$\sigma = R / 6 \tag{2}$$

Thus

$$K(i) = \exp(-18(i - M)^2 / R^2) \tag{3}$$

where K is the kernels of the template. Without loss of generality, we choose $A = 1$. Figure 2 shows the desired template intensity histogram obtained from the 20 desired retinal images.

2.3. Automatic Quality Measure of Retinal Images Using the Quality Index

To measure the over-all quality of retinal image, quantitatively and objectively, we compute the convolution of the intensity histogram (***H***) of a retinal image with the template histogram (***K***), that is,

$$\begin{aligned} C &= \mathbf{K} \cdot \mathbf{H} \\ &= \sum_{i=0}^{255} K(i) * H(i) \end{aligned} \tag{4}$$

where $K(i)$ is the coefficient of the ith kernel of the template histogram, and $H(i)$ is the number of pixels with intensity value of i. It is seen that the more the correlation between ***K*** and ***H*** is, the higher the value C will be. When $H(i)$ has exact the same shape as the template histogram $K(i)$, this convolution gives in the maximum value of C

$$\begin{aligned} C_{max} &= \sum_{i=0}^{255} K(i) * H(i) \\ &= A * \sum_{i=0}^{255} \exp(-(i-M)^2 / \sigma^2) \end{aligned} \tag{5}$$

*The range of value of intensity axis of all the histograms (1-256) corresponds to 0-255.

For an image size of 512 x 512 (pixels), and the diameter of the retina of 512 (pixels), the total retinal pixels is

$$N = \pi * (512/2)^2 \approx 205888 \text{ (pixels)} \tag{6}$$

Thus, the peak A of the Gaussian curve can be calculated by:

$$\sum_{i=0}^{255} A * \exp(-(i-M)^2/2\sigma^2) = N$$

or,

$$A = N / \sum_{i=0}^{255} \exp(-(i-M)^2/2\sigma^2) \tag{7}$$

The values of M and R of Eqs. (2)and (7) can be calculated from the 20 desired images, and they are $M = 100$, $R = 80$ ($\sigma = 13.3333$) . From Eq. (7), $A \approx 6200$ (pixels). C_{max} can now be calculated using Eq. (5), i. e.,

$$C_{max} = A * \sum_{i=0}^{255} \exp(-(i-M)^2/\sigma^2) \approx 1.6 * 10^5 \tag{8}$$

When there is no or very little correlation between the image histogram and the template histogram, C is expected to be equal or close to zero. That is, $C_{min} \approx 0$, indicating that the image is of extremely poor quality or equivalently all the three quality parameters are far from their desired values. By dividing C by C_{max}, we define a quality index Q to be

$$Q = C / C_{max} \tag{9}$$

As we can see, if $C = C_{max}$, then $Q_{max} = 1$, indicating an excellent quality retinal image. On the other hand, when $C = 0$, then $Q_{min} = 0$, indicating a very poor or bad quality retinal image.

3. EXPERIMENTS AND RESULTS

A set of retinal images of different quality given in Figure 1a, c, e, g were used to test this quality measure scheme using the quality index Q defined in Eq. (9). The values of Q of these images are $Q_a = 0.925$, $Q_c = 0.55$, $Q_e = 0.46$, and $Q_g = 0.15$, indicating that among the four images, image of Figure 1a having highest quality, and image of Figure 1g the lowest. Since images 1c, 1e, 1g were created from image of Figure 1a by lowing its brightness, contrast, and *SNR*, respectively. Thus their qualities are expected to be lower than their original, as indeed shown by the quality index Q values. Additional examples of image quality measure using Q are given in Figure 3. The results are also in agreement with human perceptions.

One of the applications of automatic image quality measure is to evaluate the performances of various image enhancement methods in improving the over-all image quality. For example, let us consider two noise removal methods. It is known that both mean filter and morphological operations can remove noise in an image but also at the same time, reduce the contrast. Unfortunately so far no one knows how to measure the tradeoffs between the noise removal and the potential contrast degradation, as well as determining which of the two methods is more suitable for a given image. At the present, which method to use is dependent upon the user's familiarity of the methods, or subjective choice. Thus, it is desirable to have a machine-objective quality measure that can be used to compare their over-all performances (noise removal and contrast maintenance). Figure 4 shows the comparison of noise removal methods between the mean filter and the morphological operation. Figures 4 (a), (c) and (e) show a retinal image with different amount of additive Gaussian noise, and the results of noise removal by using a 5 x 5 mean filter and the morphological operation, and their intensity histograms are shown in Figures 4 (b), (d), and (f), respectively. We see that the mean filter method improved the *SNR* more than the morphological operation, however, it produced a lower contrast image. From the values of the quality indexes shown in Table 1, we also see that the over-all performance of the former is slightly poorer than that of the latter. As a second comparison example, Figure 5 shows the comparison between the performances of the histogram equalization method and the direct image brightness and contrast enhancement. Both methods enhance the image brightness and contrast characteristics. To avoid personal preferences and subjective judgments, we found that use of Q in this situation is particularly helpful. The Two comparison examples are summarized and given in Tables 1 and 2.

Table 1. Comparison of two noise removal methods using index Q

Image	M	R	SNR(dB)	Q
Original noisy image (Fig.4a)	118	170	13.5	0.44
Noise removed by a 5x5 mean filter (Fig.4b)	118	110	21.7	0.63
Noise removed by a morphological operation (Fig. 4c)	118	114	21.2	0.64

Table 2. Comparison of two contrast improvement methods using index Q.

Image	M	R	SNR(dB)	Q
Original dark image (Fig.5a)	28	80	31.2	0.19
Enhanced by equalization (Fig.5b)	118	130	25.6	0.52
Enhanced by direct brightness & contrast (Fig.5c)	120	110	24.3	0.48

4. CONCLUSION

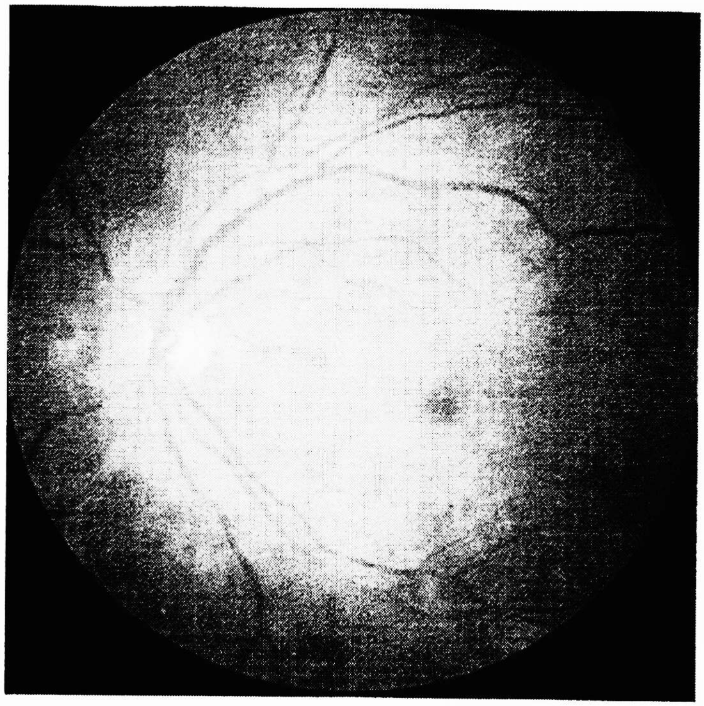
An automatic objectively-defined image quality measure for measuring retinal images has been presented. This measure is useful not only in assessing the quality of an image, but also in selecting appropriate image improvement methods for a given image, as well as in measuring how much improvement has actually been offered by those methods. If the Q of an image is decreased considerably after a well-intended image enhancement method is applied, this tells us that this method is not suitable for the given image and/or the application, and that should not be used. Although retinal images are used in this study, with proper modifications, this method is applicable and could be extended to other types of medical images.

ACKNOWLEDGEMENT

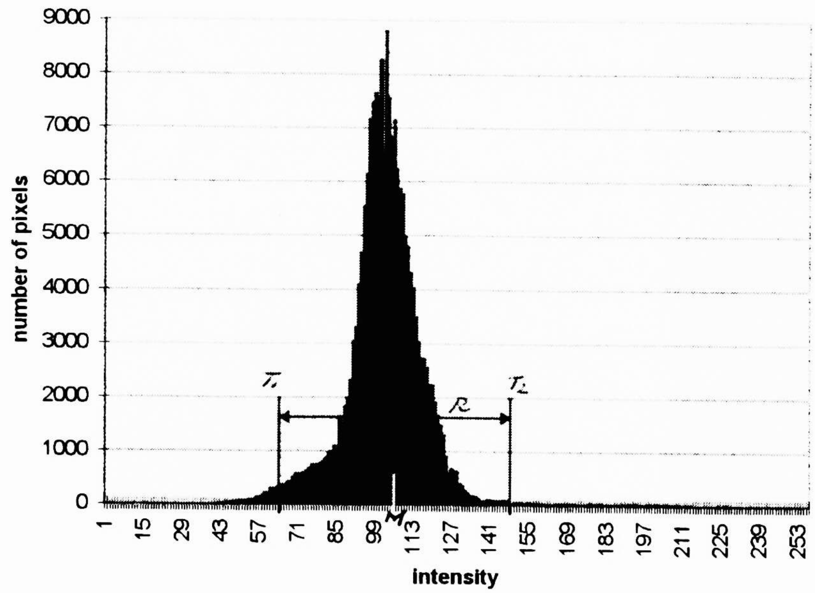
The study is supported by a grant (Grant number U10EY09898) from the National Eye Institute. The authors wish to thank Dr. Ronald Kingsley and Dana Russell for their assistance.

REFERENCES

1. I.T. Young, J.J. Gerbrands, L.J. van Vliet. Fundamentals of Image Processing. *The Pattern Recognition group* (PH), Lorentzweg 1, 2628 CJ Delft, The Netherlands.
2. Lee, SC. Computer Diagnosis of Diabetic Retinopathy. *The 15th International Diabetes Federation Congree*, Nov 6-11, 1994, Kobe, Japan. Page 365.
3. Lee, SC. Diagnosis of Diabetic Retinopathy by Computer Vision. *Proceedings of AAAI Spring Symposium on Medical Applications for Computer Vision*. March 21-23, 1994.
4. Lee, SC. Early Diagnosis on Retinopathy of Diabetics Using Computerized Imaging Techniques. *1996 SCBA Conference Record*, Nov. 23-24, 1996.
5. Lee, SC. A Real-time High-Resolution Color Imaging System to Aid Ophthalmologist in Diagnosing/Grading Diabetic Retinopathy. *57th Annual Meeting and Scientific Sessions of American Diabetes Association*, Boston, Mass. June 21-24, 1997. Abstract in *Diabetes*, Vol. 46, Supplement 1, May 1997.
6. Lee, SC. Screening for Early Diabetic Retinopathy by a High Resolution Computer Vision System. *1997 International Diabetes Federation Congree*, Helsinki, Finland, July 20-25, 1997. Abstract in *Diabetologia*, Vol. 40, Supplement 1. 1997.
7. Lee, SC. Computer Recognition and Diagnosis of Diabetic Retinopathy. *Beijing International Conference on Diabetes in Elderly*. Sep. 26-28, 1997.
8. Lee, SC, Wang, Y. A fast Method for Automated Detection of Blood Vessels in Retinal Images. The 31st Asilomar Conference on Signals, System, and Computers. Nov 2-5, 1997.
9. Lee, SC et al. Comparison of Diagnosis of Non-proliferative Diabetic Retinopathy between Human Experts and a Computer Vision System. 58th Annual Meeting and Scientific Sessions of American Diabetes Association. Chicago, Il, June 13-16, 1998.

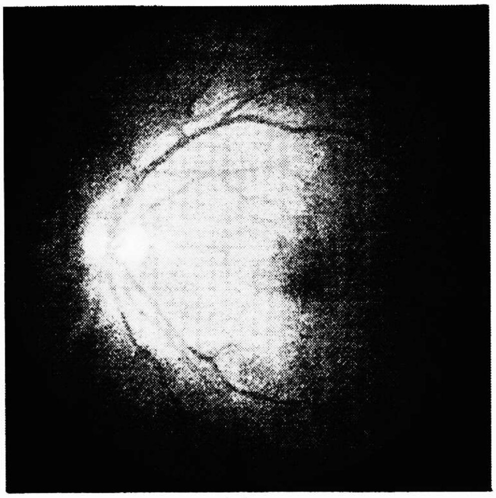


(a)

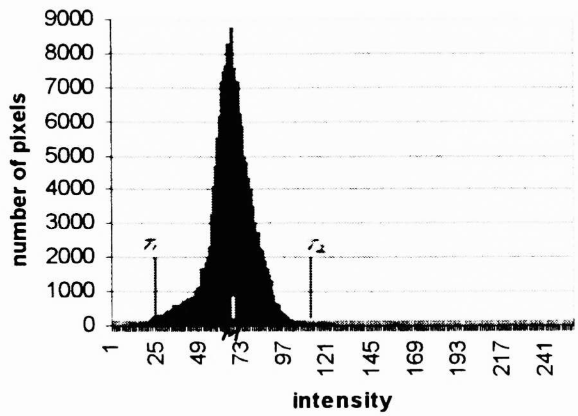


(b)

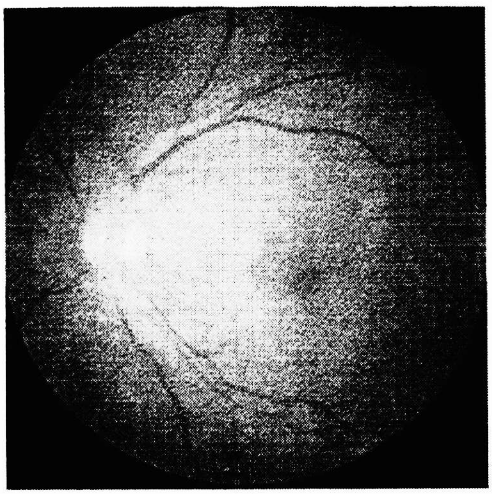
Figure 1. (a) A typical good quality retinal image (desired image). (b) Intensity histogram. M is the mean of over-all pixel intensities, and R is the range of the retinal band. We use notation M_a and R_a to present the mean value and the range of retinal band of image (a) in Figure 1. M_b and R_b are the mean value and the range of retinal band of image (b) in Figure 1, and so on. $M_a = 105$, $R_a = 85$.



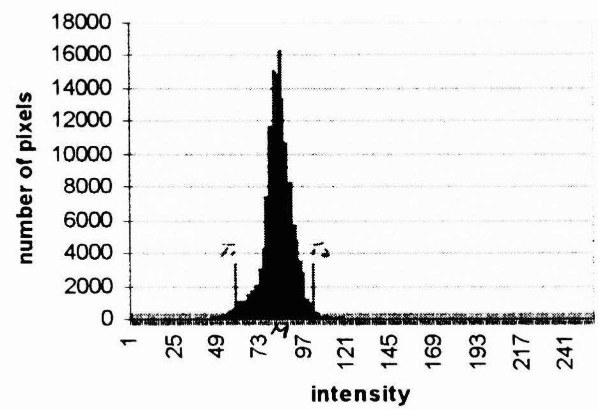
(c)



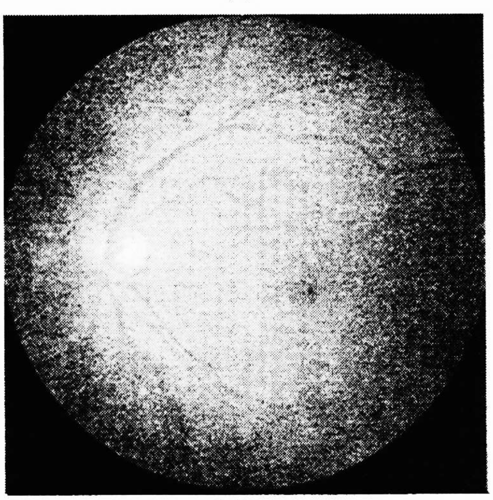
(d)



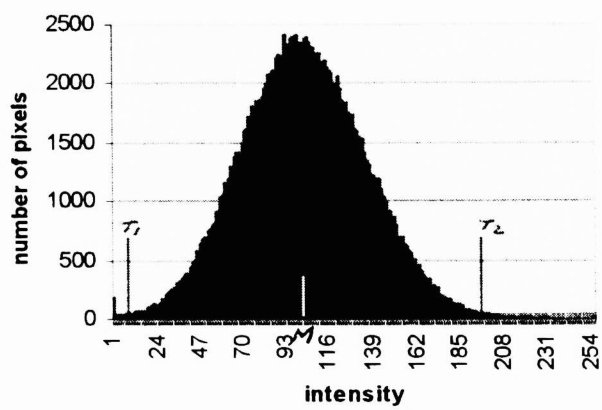
(e)



(f)

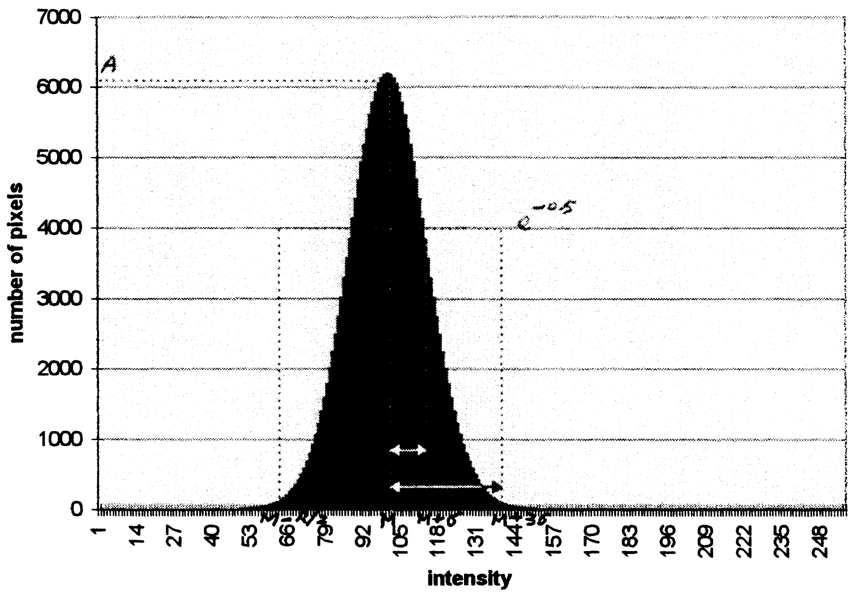


(g)

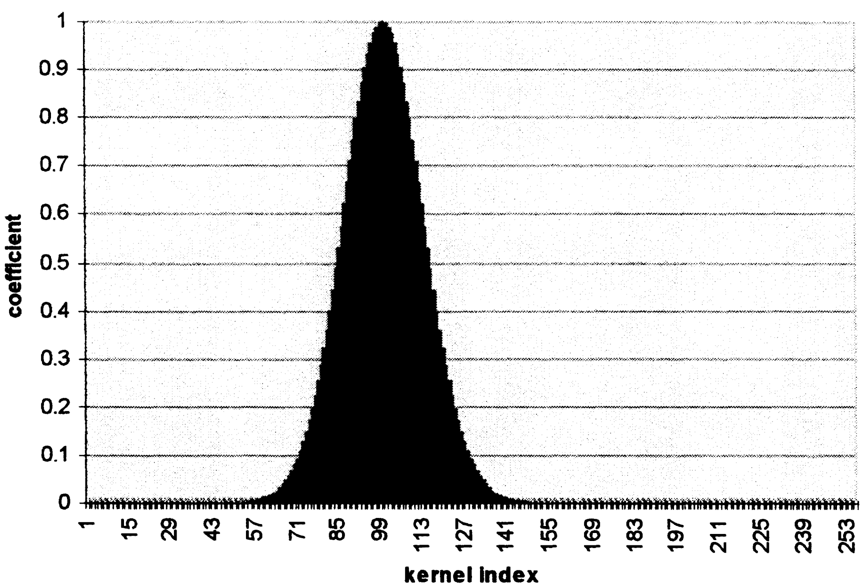


(h)

Figure 1(Cont'). (c) Same image as (a) with decreased brightness level by 35. $M_c = M_a - 35$. $R_c = R_a$. (d) Intensity histogram of (c). (e) Same image as (a) with decreased contrast by 35. $M_e < M_a$, $R_e - R_a = 35$. (f) Intensity histogram of (e). (g) Same image with decrease *SNR* by adding addictive Gaussian noise with zero mean and constant variance. $M_g = M_a$. $R_g \gg R_a$.



(a)



(b)

Figure 2. (a) Guassian distribution of the template intensity histogram of retinal images.
(b) Matched filter with the same shape as the template profile in (a).

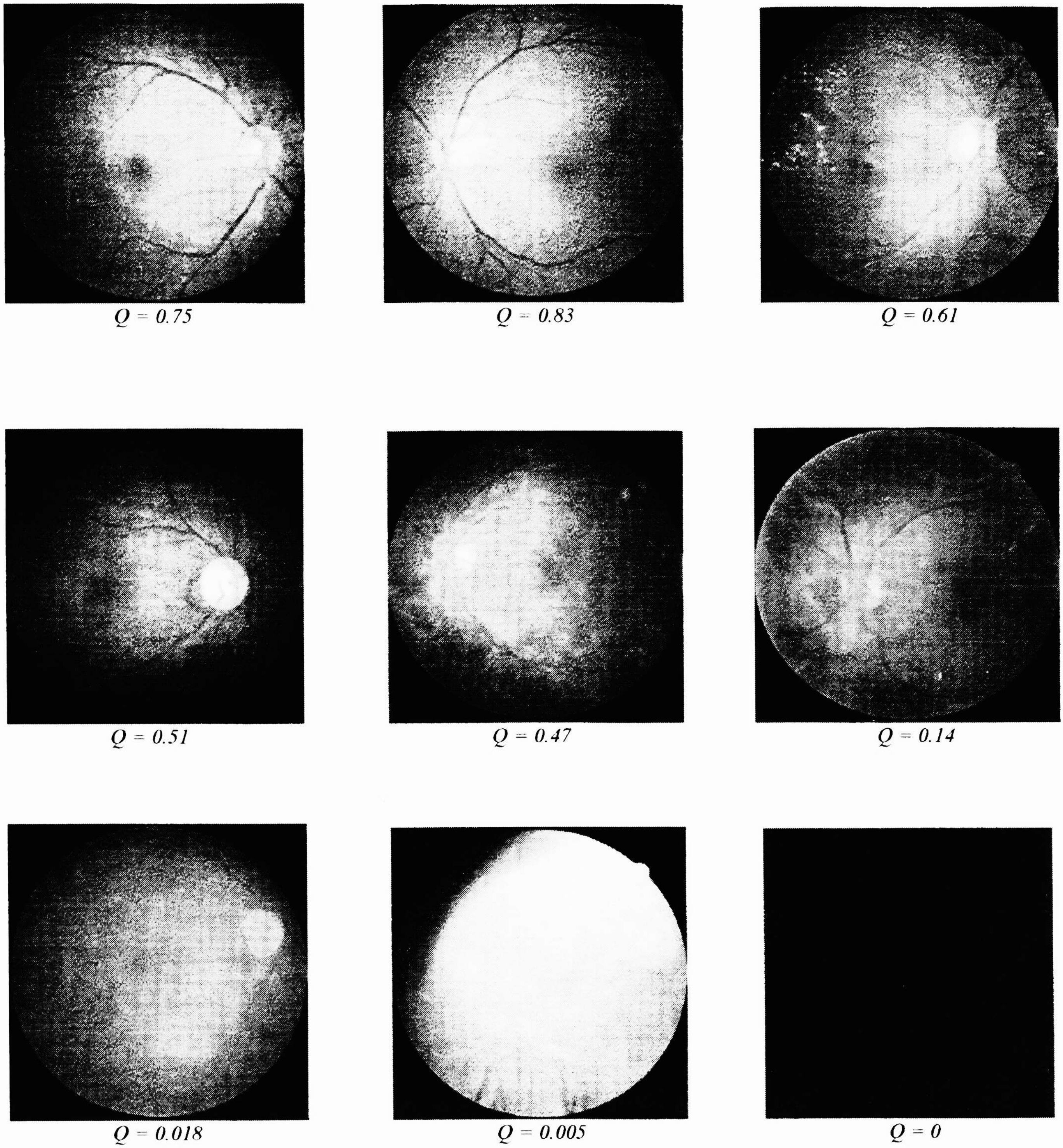


Figure 3. Experiment results of image quality measure by quality index.

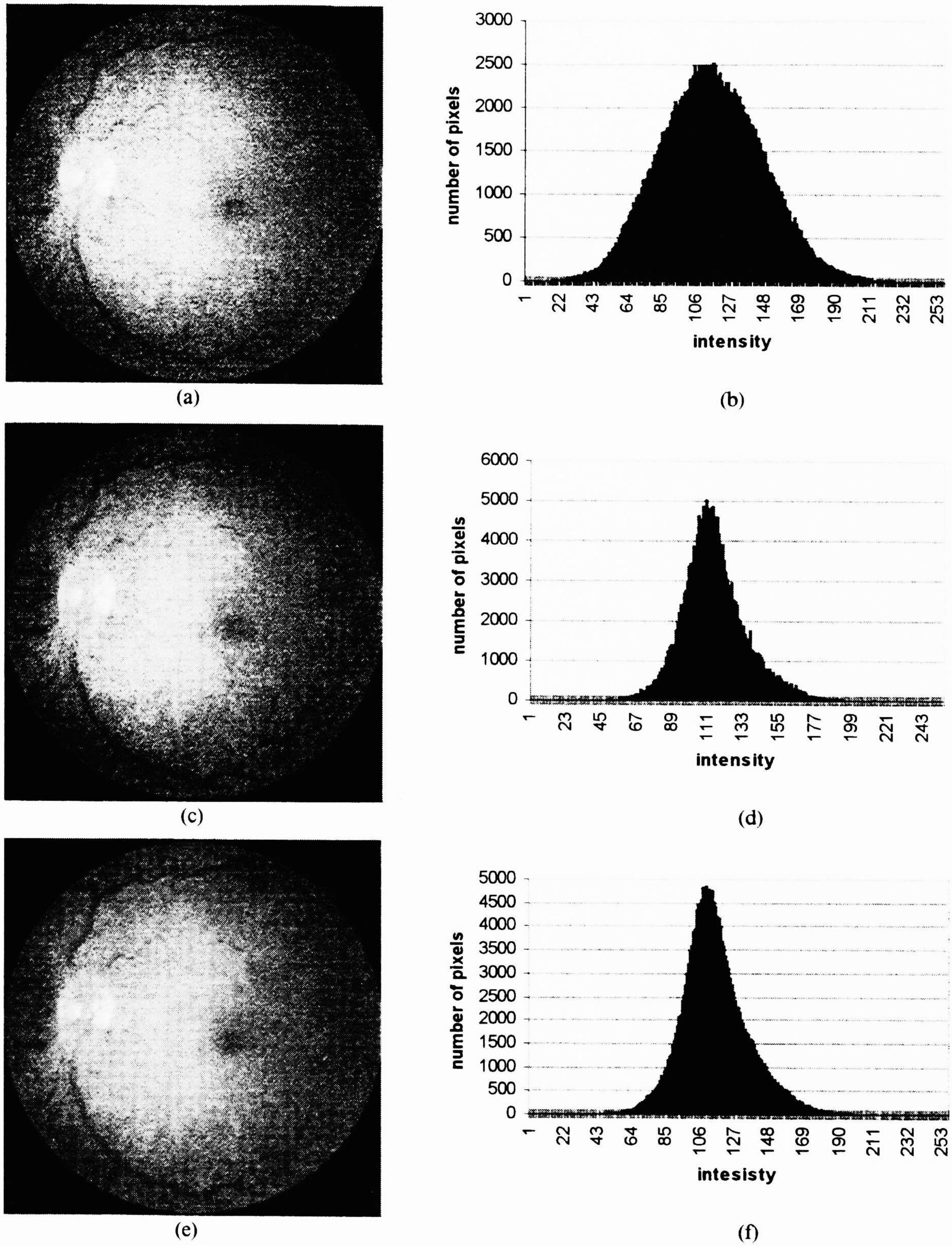


Figure 4. (a) An image with additive Gaussian noise. M_a=118, R_a=170, SNR_a=13.5dB, Q_a=0.44. (b) Histogram of (a). (c) Result of noise removal using 5x5 mean filter. M_c=118, R_a=110, SNR_c=21.7dB, Q_c=0.63. (d) Histogram of (c). (e) Result of noise removal by morphological operation. M_e=118, R_e=114, SNR_e=21.2dB, Q_e=0.64. (f) Histogram of (e).

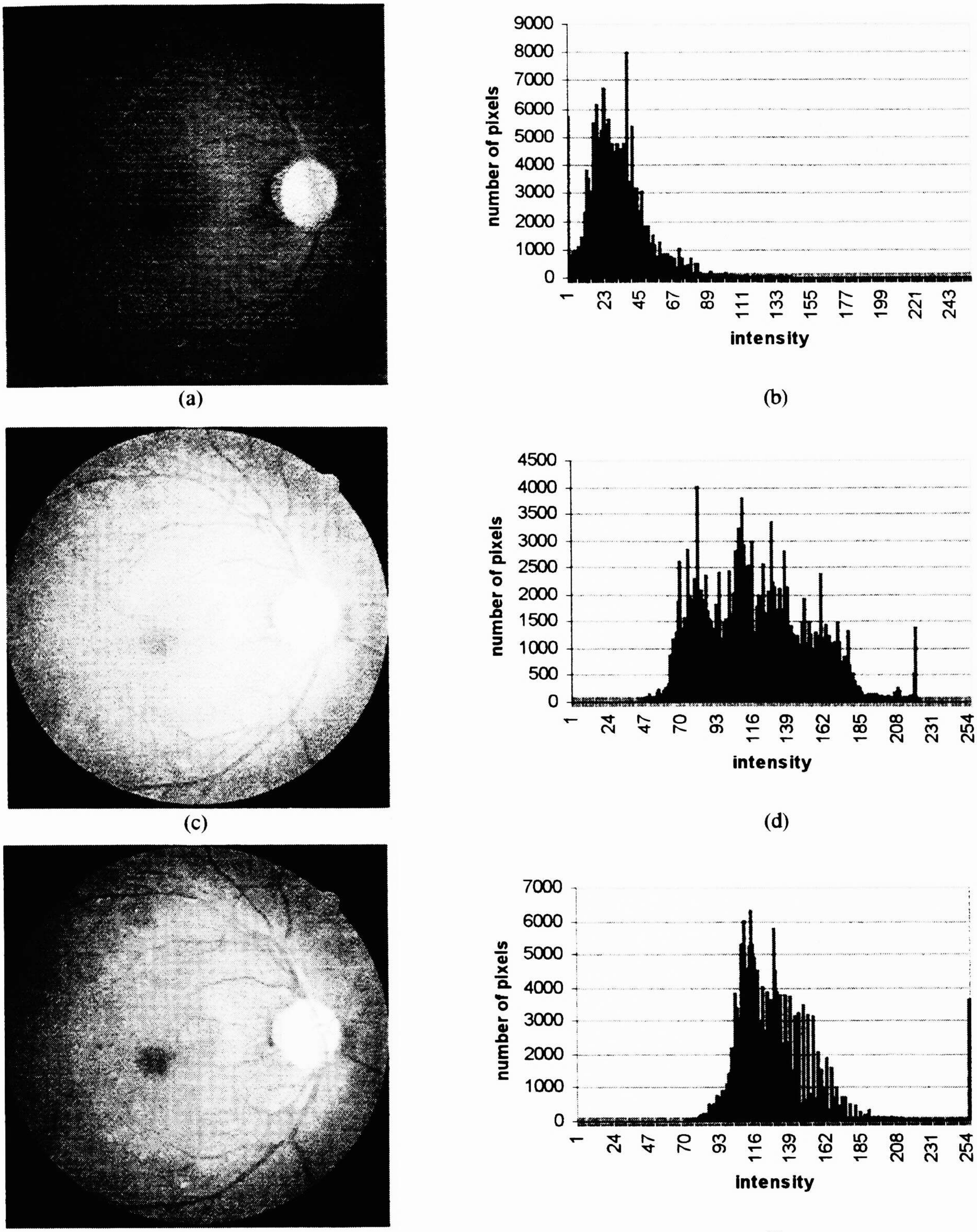


Figure 5. (a) A originally dark image. M_a=28, R_a=80, SNR_a=31.2dB, Q_a=0.19. (b) Intensity histogram of (a).
(c) Result of enhancement by image equalization. M_c=118, R_c=130, SNR_c=25.6dB, Q_c=0.52. (d) Intensity histogram of (c).
(e) Result of enhancement by direct brightness and contrast enhancements. M_e=120, R_e=110, SNR_e=24.3dB, Q_e=0.48.
(f) Histogram of (e).