Adaptive-Neighborhood Histogram Equalization of Color Images

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Abstract

Histogram equalization (HE) is one of the simplest and most effective techniques for enhancing gray-level images. For color images, HE becomes a more difficult task, due to the vectorial nature of data. We propose a new method for color image enhancement that uses two hierarchical levels of HE: global and local. In order to preserve the hue, equalization is only applied to intensities. For each pixel (called the "seed" when being processed) a variable-sized, variable-shaped neighborhood is determined to contain pixels that are "similar" to the seed. Then, the histogram of the region is stretched to a range that is computed with respect to the statistical parameters of the region (mean and variance) and to the global HE function (of intensities), and only the seed pixel is given a new intensity value. We applied the proposed color HE method to various images and observed the results to be subjectively "pleasant to the human eye", with emphasized details, preserved colors, and with the histogram of intensities close to the ideal uniform one. The results compared favorably with those of three other methods (histogram explosion, histogram decimation, and three-dimensional histogram equalization) in terms of subjective visual quality.

Keywords: Histogram equalization, Color image processing, Color image enhancement, Adaptive-neighborhood image processing.

1 Introduction

Histogram equalization (HE) is one of the simplest, commonly used, and effective techniques for enhancing gray-level images. The hypotheses underlying HE are that the pixels are independent random variables with identical probability density functions (PDF), and that the image is a realization of an ergodic random field. Hence, the nearer an image histogram is to a uniform distribution, the more informative the image is. It is known from probability theory that for any random variable ξ characterized by the cumulative distribution function (CDF) $F_\xi(x)$, the random variable $\eta = F_\xi(\xi)$ is uniformly distributed over $(0, 1)$ [1]. This result is used to achieve HE of gray-level images. The major drawback of this simple approach is the effect of gray-level quantization: in the continuous case, extending the PDF range raises no problems; in the discrete case, this technique is not able to increase the number of gray levels (e.g., 32 values dispersed over a range of 256 levels will remain as 32 discrete levels, albeit more distant from one another). Thus, the histogram of the output image is only approximately uniform. The similarity between the output histogram and an ideal uniform distribution is related to the number of distinct gray levels in the original image. However, in practice, HE produces images with increased contrast, which may appear to be enhanced and more "readable".

When dealing with color images, HE becomes a much more difficult task, due to the vectorial nature of the data: each pixel is represented by a vector with three components, i.e., the amount of red (R), green (G), and blue (B) that compose the given color. It is well-known that, in general, the three components are mutually correlated. Hence, attempting to equalize the histogram of each channel separately would lead to an incorrect result by neglecting the inter-component correlation. Therefore, techniques to equalize (or modify) the histogram of a color image by joint processing of the three channels have been developed.

We should add at this point that HE is just one technique among many others for image enhancement, mainly useful when enhancement is aimed at improving visibility and detectability of image features; enhancement for preference would require specific effects that might alter the characteristics of the image to suit individual preferences. Regardless, even enhancement for preference could benefit from HE, with HE being followed by an appropriate second step [1, 2, 3].

There are two main approaches to HE of color images: the first one considers processing of color image data in the original RGB space. The "3-D histogram equalization" method proposed by Trahanias and Venetsanopoulos [4] consists of three-dimensional (3-D) histogram specification in the RGB cube, with the output histogram being uniform. The 3-D CDF $F_{RGB}(r, g, b)$ of the original image, as well as an ideal, uniform CDF $\bar{F}_{R',G',B'}(r', g', b')$ are computed. Then, each pixel $[R, G, B]$ is assigned the smallest value $[R', G', B']$ for which $\bar{F}_{R',G',B'}(R', G', B') \geq F_{RGB}(R, G, B)$. Since these conditions are ambiguous, allowing more than one solution, a method to determine R', G', and B' by sequentially incrementing (or decrementing) R, G, and B is further proposed. Thus the output 3-D histogram gets as close as possible to a uniform 3-D distribution.

More recently, Mlsna and Rodríguez [5] proposed a 3-D technique that exploits the full 3-D gamut, and called the method "histogram explosion". For each point in the RGB cube corresponding to an image color, a ray that starts from some central point (which is usually chosen as the average color of the image) is defined to pass through that point. Then, all points within a threshold distance of the ray are projected on to the ray. In this way, a 1-D histogram along the ray is created. By modifying (equalizing) the 1-D histogram, the new color value for the original point is determined. By this technique, color points are almost uniformly spread in the color space. Another version of this method [6] deals with colors represented in the Commission Internationale de l'Eclairage CIE-LUV space.

The "histogram decimation" technique [6, 7] attempts to uniformly scatter the color points over the full 3-D gamut by means of an iterative algorithm. The algorithm starts by setting the full 3-D color space as the current space. Each iteration consists of two steps: in the first step, all color points within the current space are shifted such that their average overlaps the geometric center of the space; in the second step the current color space is divided into eight equally-sized subspaces. Each newly-created color subspace is set as the current space for the next iteration, and so on. The algorithm stops when the subspace size has reached its minimum value. Thus, the color points are spread to occupy the full gamut.

All of these methods, although interesting, are in general computationally expensive and have the drawback of modifying color hues. In many cases, the latter may lead to results that are unpleasant to a human observer, since it is known that the human visual system is extremely sensitive to shifts in hue.

The second class of methods considers equalization in other perceptual color spaces, mainly the Hue, Saturation, Intensity (HSI) space [8, 9, 10]. The advantage of representing colors using HSI is that one can consider modifications of only intensity, or both intensity and saturation, leaving the hue unmodified. Thus, the drawback of the previously presented methods is overcome. Pitas and Kiniklis [9] present a method to jointly equalize intensity and saturation. However, it is mentioned that modification of saturation is not advised, since it results in unnatural output images. A recent method reports on histogram modification in the color difference C–Y space [11, 12], where the authors propose modifications of saturation and hue only based on a priori knowledge of the image content. HE of the intensity (brightness) component only appears to be effective: it has a low computational cost (the same as in the case of gray-level images) and yields results that are visually correct, since it does not create colors that are not natural. An improvement to this simple technique is proposed by Rodríguez and Yang [10], who investigate the effect of quantizing brightness to a predefined number of bins before equalization.

Starting from the constraint that only the brightness component is to be equalized, we propose in this paper a new method for HE of color images via the adaptive-neighborhood approach [13, 14, 15, 16, 17, 18, 19, 20]. The method is designed to increase the number of intensity levels in the image by taking into account values of pixels within a certain neighborhood when computing the new intensity value of a pixel. The neighborhood is determined adaptively for each pixel in the image by a region growing algorithm, rather than forcing it to a predefined shape and size. Details of the proposed method are presented in Section 2. Section 3 provides the results obtained by the proposed technique and comparison with the results of other techniques. In Section 4, some conclusions are presented.

2 Adaptive-neighborhood histogram equalization (ANHE) of color images

In this section, a new method for HE of color images using the adaptive-neighborhood approach is presented. The adaptive-neighborhood paradigm has been used to filter signal-dependent and signal-independent noise in gray-level images [13, 14, 15, 16], and has been adapted to the case of noisy color images [17]. The paradigm was also used to achieve HE of gray-level images [18] and enhancement of medical images [19]. Regardless of the application, the idea is to determine for *every pixel* in the image (called the “seed” when being processed) a variable-sized, variable-shaped neighborhood by a region growing procedure. The neighborhood contains only those spatially-connected pixels that are “similar” to the seed. The similarity between two pixels is generally assessed by comparing the Euclidean distance between the values of the two pixels with a threshold value. Then, the pixels in the adaptive neighborhood are used to derive the new value for the seed location. It should be noted that the procedure is applied to *every pixel* in the image: each pixel becomes the seed for region growing when being processed.

The proposed algorithm [20] combines together several ideas:

- The hue must be preserved; thus, equalization will be applied only to the brightness component of the color image. One may argue that this principle does not always correspond to real-world situations. For instance, in color reproduction applications [21, 22], it is preferable to shift hues to desired values. Still, HE is a basic enhancement operation that is assumed to yield correct results without prior information about the image content. As mentioned above, HE can be the first step of a more elaborate chain of enhancement steps that also control hue shifts. Thus, in order to avoid uncontrolled hue deviation, it is preferable that HE does not alter hues in any way.

- A good way of extending the number of levels is to take into account the neighboring values, i.e., to compute the new value as a function of a few local variables (as in the case of filtering with local kernels) and not as a function of only the original value of the pixel being processed.

- The neighborhood that contributes to the derivation of the new value of a pixel must be chosen adaptively, for reasons of uniformity. The advantage of using an adaptive neighborhood instead of a fixed one is that stationarity is guaranteed within such neighborhoods. Only pixels that have values similar to the seed are chosen to contribute to its output value. By such an approach, local details are emphasized.

- Generally, a well–balanced image is one with the average intensity at the middle of the gamut; therefore, the global histogram of the intensity image is to be taken into account when computing the new value of a pixel. In the case of images for which the above remark does not stand true, point operators other than the global HE function can be used (see Section 3).

The steps of the ANHE algorithm for color images are shown in the flowchart in Figure 1 and detailed in the following subsections.

2.1 Computation of the global HE function

In the first step, the intensity image I is computed from the three color channels R, G, and B. Since I is equivalent to a gray-level image, its 1-D intensity histogram (or PDF) can be computed as

$$h_I(i) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \delta(I(m,n) - i), \qquad i = 0, \ldots, L-1,$$

where M and N are the number of rows and columns in the image, L is the number of levels in the intensity image (usually, $L = 256$), and

$$\delta(j) = \begin{cases} 1 & \text{if } j = 0 \\ 0 & \text{otherwise.} \end{cases}$$

Based on the histogram, the global HE function F_I is then determined:

$$F_I(i) = \left\lfloor (L-1) \times \sum_{j=0}^{i} h_I(j) \right\rfloor, \qquad i = 0, \ldots, L-1.$$

For each value $I(m,n)$, $F_I(I(m,n))$ stores the new value as given by the global HE technique.

2.2 Histogram equalization using the adaptive neighborhood

As stated before, for each pixel in the intensity image I, an adaptive neighborhood (region) is to be determined to contribute to the computation of its new value. Pixels belonging to the region have to fulfill two conditions:

- to have the intensity value close to that of the seed;
- to be spatially connected to the seed.

2.2.1 Adaptive region growing

The region-growing procedure [13, 14] consists of evaluating the absolute difference d_{kl} between each of the eight-connected neighbors $I(k,l)$ of the seed and the seed $I(i,j)$ as

$$d_{kl} = |I(k,l) - I(i,j)|.$$

Pixels $I(k,l)$ having $d_{kl} \leq T$, where T is a fixed, predefined threshold are included in the region. The algorithm then proceeds by checking all eight-connected neighbors of the newly-included pixels in the same manner and stops when either the inclusion criterion is no longer fulfilled for any neighboring pixel, or the number of included pixels equals a predefined upper-limit N_{max}. The region size may be limited in order to keep the computational cost of the algorithm within practical limits.

Although the choice of T is not critical, it is important to have its value between some given limits depending upon the image: a large value of T would lead to regions (neighborhoods) not representative of the object to which a seed belongs (uniformity is not preserved), whereas too small values of T would result in very small regions that are inadequate to support statistical processing. Tests conducted on many images support the observation that an acceptable range for T is $T \in [20, 40]$. If, however, for the chosen T, the region has not grown adequately (i.e., it contains less than a predefined lower-limit of N_{min} pixels), T is increased and the region-growing procedure is repeated.

2.2.2 Modification of the region intensity histogram

After the region has been grown, its intensity histogram h_{reg} is computed. Due to the thresholding step in the region-growing procedure, the intensity histogram of the region will be narrow, i.e., it will have non-zero components in a limited interval. In order to compute the new intensity value for the seed, the intensity histogram has to be modified. It is obvious that attempting to equalize the intensity histogram of the region over the whole gamut would lead to incorrect results. This is because a few intensity levels within a limited range would get scattered from black to white. Since the purpose of this step is to reinforce details, we chose not to equalize, but to stretch the intensity histogram of the region to a range $[i_{min}, i_{max}]$. The values of i_{min} and i_{max} must be computed with respect to the data in the intensity histogram of the region, and, as mentioned before, with further reference to the global HE function F_I.

In order to determine the limits of the range to stretch the intensity histogram of the region, the mean μ_{reg} and standard deviation σ_{reg} of the population of pixels within the region are computed. Then, we take:

$$i_{min} = F_I(\mu_{reg}) - \kappa\sigma_{reg},$$

and

$$i_{max} = F_I(\mu_{reg}) + \kappa\sigma_{reg},$$

where κ is a constant (for the entire image) to be chosen by the user. Thus, the new intensity value of the seed pixel is computed as

$$I'(i,j) = \left[i_{min} + (i_{max} - i_{min}) \times F_{reg}(I(i,j))\right],$$

where F_{reg} is the CDF of the region computed from the intensity histogram h_{reg}. We stress that *only the seed intensity* is updated according to the modified histogram of the region.

The choice of the values of i_{min} and i_{max} may be described as follows: the whole histogram of the region is to be shifted such that the mean μ_{reg} overlaps its value given by the global HE function $F_I(\mu_{reg})$ and is further extended to a range that is proportional to the standard deviation of the pixels within the region. The need for histogram shifting can be related to the fact that we want the resulting image to be well-balanced, i.e., to have luminosities globally spread from black to white. This can only be achieved by the use of the global HE function. If, in the limit case, we impose the maximum number of pixels in the region $N_{max} = 1$, the outcome of our method would be the image with the equalized histogram of intensities.

The range width is proposed to be proportional to the standard deviation σ_{reg} rather than being fixed for the following reason: we should not amplify very small variations that cannot be interpreted as significant details, and are most probably due to imperfections of the image acquisition system. For instance, a blue sky area in an image has to remain uniform if there are no clouds. On the contrary, if the nonuniformity of the region is important, i.e., there are significant details in the region, we want to emphasize them by extending the range over which the histogram of the region is stretched. In Figure 2, the initial and modified intensity histograms of a region of an image are presented.

The parameter κ, which has to be chosen by the user, controls the width of the range over which the region histogram is expanded, i.e., it controls the "amplification" of details. For normal-contrast images, we suggest to choose $\kappa \in [3, 7]$; a larger value for κ is indicated for low-contrast images. κ has to be set with respect to the threshold T used in the region-growing procedure. Indeed, if regions are grown with a small T, then the standard deviation of the pixel population within a region σ_{reg} would be small, and thus one should set κ to a larger value in order to obtain a visible emphasis of details.

The ANHE procedure for color images consists of a two-level HE procedure: global and local. After the new intensity value I' has been computed, the new values of the color components R', G', and B' of a pixel are determined by scaling the old values R, G, and B with the factor I'/I. Thus, the color hues are preserved, and only brightness is modified. The overall procedural flowchart of ANHE for color images is shown in Figure 1.

3 Results and discussion

In this section, the results of ANHE of color images are provided and compared with those of other HE techniques for color images.

The user of the results of HE is, in most cases, the human visual system. Thus, it is difficult to derive objective criteria to assess the effectiveness of such an operation. Some authors have proposed, as a measure of quality, the difference between the histogram of the output image and an ideal 3-D uniform histogram[6, 7]. Due to the fact that our method introduces more levels of brightness, we get histograms much closer to the ideally uniform one than those provided by other methods. Nevertheless, our goal is an optimal expansion of the existing values in the whole 3-D color space *with constraints*, rather than free, unconstrained equalization, due to the artifacts of the latter. A comparison between the outcomes of different HE techniques for color images can be done only subjectively, by a human observer.

Figures 3, 4, 5, and 6 present the original versions of four test images (obtained from the ftp site ipl.rpi.edu) and their processed versions as given by ANHE and four other techniques. Figures 7 and 8 present the original and the ANHE versions of six more images. The outcome of the brightness-only global HE method is well contrasted and provides natural colors, but the details are not emphasized. Equalization of each channel independently creates false colors since it is performed separately within three different contexts, i.e., the HE function on each channel is computed with no attention paid to the two other channels.

After "3-D histogram equalization", the images tend to become too bright, and colors faint, due to color modification along the main diagonal of the RGB cube. The "histogram decimation" technique provided the poorest results in terms of hue modification, leading to the appearance of many unnatural colors in the image. This is because of the scattering of color points in the RGB cube with the aim of obtaining a uniform distribution with no respect to the original hues. One other drawback of this technique is that colors that are originally close may be treated in different manners, due to the fact that they could be assigned to different subspaces; thus, they may severely differ in the resulted equalized image.

"Histogram explosion" provided acceptable results. The main drawback of the method is the uncontrolled color hue modification. In spite of the fact that the shifts in hue created by "exploding" the histogram could result in colors that may be pleasant to the human eye, some of the newly-created colors gave pictures an unnatural quality.

The images equalized with the ANHE method were very good in terms of visual appearance. The ANHE features of color preservation, uniform spreading of luminosities from black to white, and detail emphasis (see Figure 9) acted together to provide good enhancement. Figure 10 shows the intensity histograms of all of the images presented in Figure 3. The histogram after ANHE is the closest to a uniform one.

After analyzing the results of tests conducted with many images, we can state that the images yielded by ANHE of color images appear to be the most pleasant to the human eye: the images retain their natural colors and the details are very well contrasted. Unlike the other techniques, the number of intensity levels is increased by ANHE, and consequently, smooth variations are maintained within objects with no false contours. Moreover, local details are slightly emphasized, which gives an overall pleasant aspect to the images. Table 1 presents the number of distinct colors in four of the test images after applying various HE techniques. As expected, the ANHE result has the maximum number of distinct colors.

Since equalization is applied to the brightness component only, the ANHE technique can be applied to gray-level images as well, without loss of effectiveness. In the case of gray-level images, there are applications when other point operators (such as piece-wise linear, logarithmic, exponential, or nonlinear operators [1]) might perform better than HE. Another alternative to HE is histogram specification, where the aim is to obtain not a uniform histogram, but one of a pre-defined shape. It is possible to take into consideration operators as above when applying ANHE to color images by chosing the function F_I to be not the global HE function but some other function that maps one gray-level to another.

In terms of computational requirements, the most efficient techniques are global equalization of brightness only and independent equalization of each channel, which is expected, due to their simplicity. The histogram decimation procedure is also fast, whereas 3–D histogram equalization and histogram explosion are computationally the most expensive procedures; moreover, these three techniques have the drawback that their processing times depend upon the number of distinct colors in the input image. The time requirement of ANHE strongly depends upon the parameter N_{max}, i.e., the maximum number of pixels allowed in a region.

Tests on various images have indicated that there is no noticeable improvement in the ANHE result if N_{max} is chosen over a limit of about 100 pixels (for a 256×384-pixel image). Table 2 summarizes the execution times for all of the algorithms run on a SUN ULTRA SPARC 10 workstation powered by a 440 MHz processor, with 1GB RAM. The computing time could be reduced by optimization of the program code and use of parallel computing systems.

4 Conclusion

We have proposed a new method for histogram equalization (HE) of color images by using an adaptive-neighborhood approach. The main idea of the algorithm is to use two levels of equalization: global and local. The new intensity of a pixel is computed with respect to the global HE function, and with respect to the values of pixels in a neighborhood that is adaptively determined for each pixel individually. The results yielded by the proposed technique are better in terms of visual quality and the number of distinct colors than those provided by other HE techniques for color images. Since the computational requirement is not very demanding, the proposed technique is a powerful tool for color image enhancement.

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Image	Original	Independent equalization	Brightness equalization	3-D histogram equalization	Histogram decimation	Histogram explosion	ANHE
"03"	33936	29226	28868	28684	32281	31976	41784
"08"	63126	55711	53672	51008	61086	60306	64536
"13"	59974	51416	51198	45618	57074	57792	66175
"22"	63145	59072	50103	56040	62126	62246	65834

Table 1: Number of distinct colors in images before and after histogram equalization.

Image	Independent equalization	Brightness equalization	3-D histogram equalization	Histogram decimation	Histogram explosion	ANHE ($N_{max} = 100$)
"03"	0.08	0.2	241.9	21.1	1167.6	31.9
"08"	0.08	0.2	873.6	123	4607.8	30.6

Table 2: Execution times (in seconds) for the various histogram equalization methods studied.

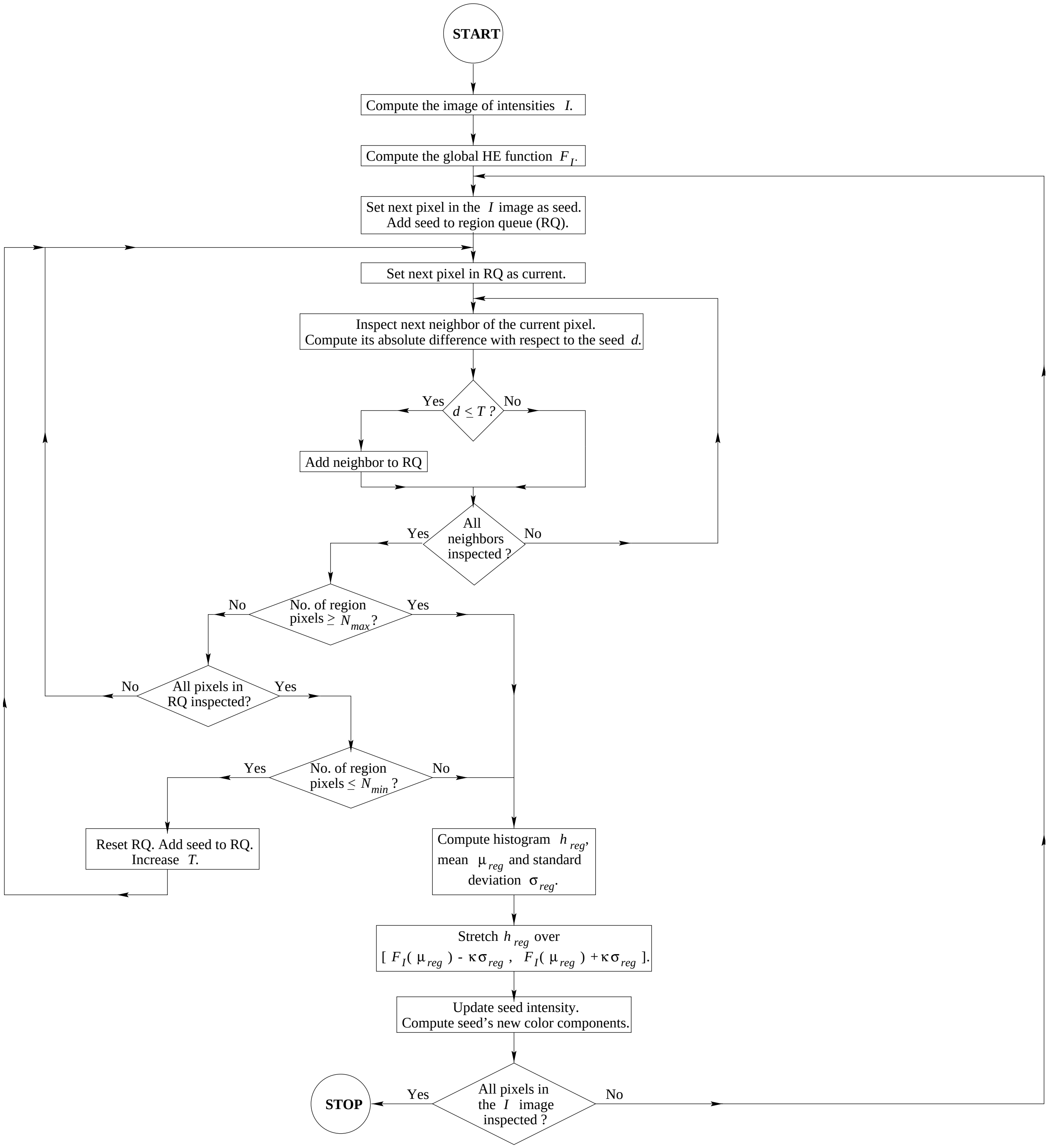


Figure 1: Flowchart of the ANHE method.

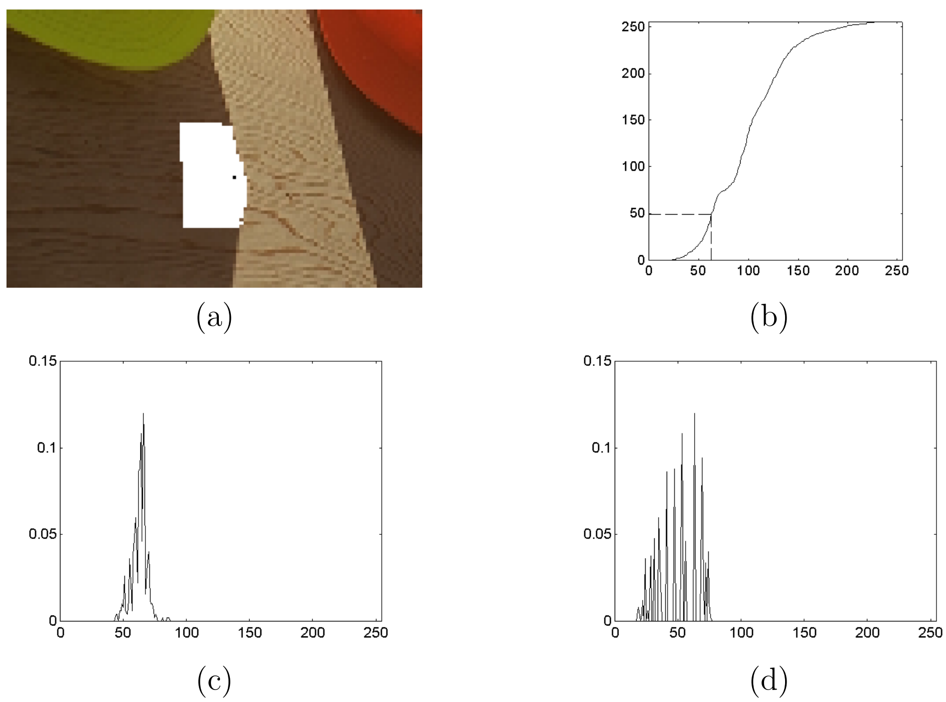


Figure 2: Steps for histogram modification of a region: (a) Region grown for seed pixel (182,139) in the “03” image in Figure 3.a having intensity value 60; the region pixels are in white, seed pixel in black. The region size is limited to $N_{max} = 500$ pixels (b) Global HE function. $F_I(63) = 47$. (c) Original histogram of the region; $\mu_{reg} = 63$, $\sigma_{reg} = 6.2$, $i_{min} = 18$, $i_{max} = 78$. (d) Histogram of the region after modification.

(a)

(b)

(c)

(d)

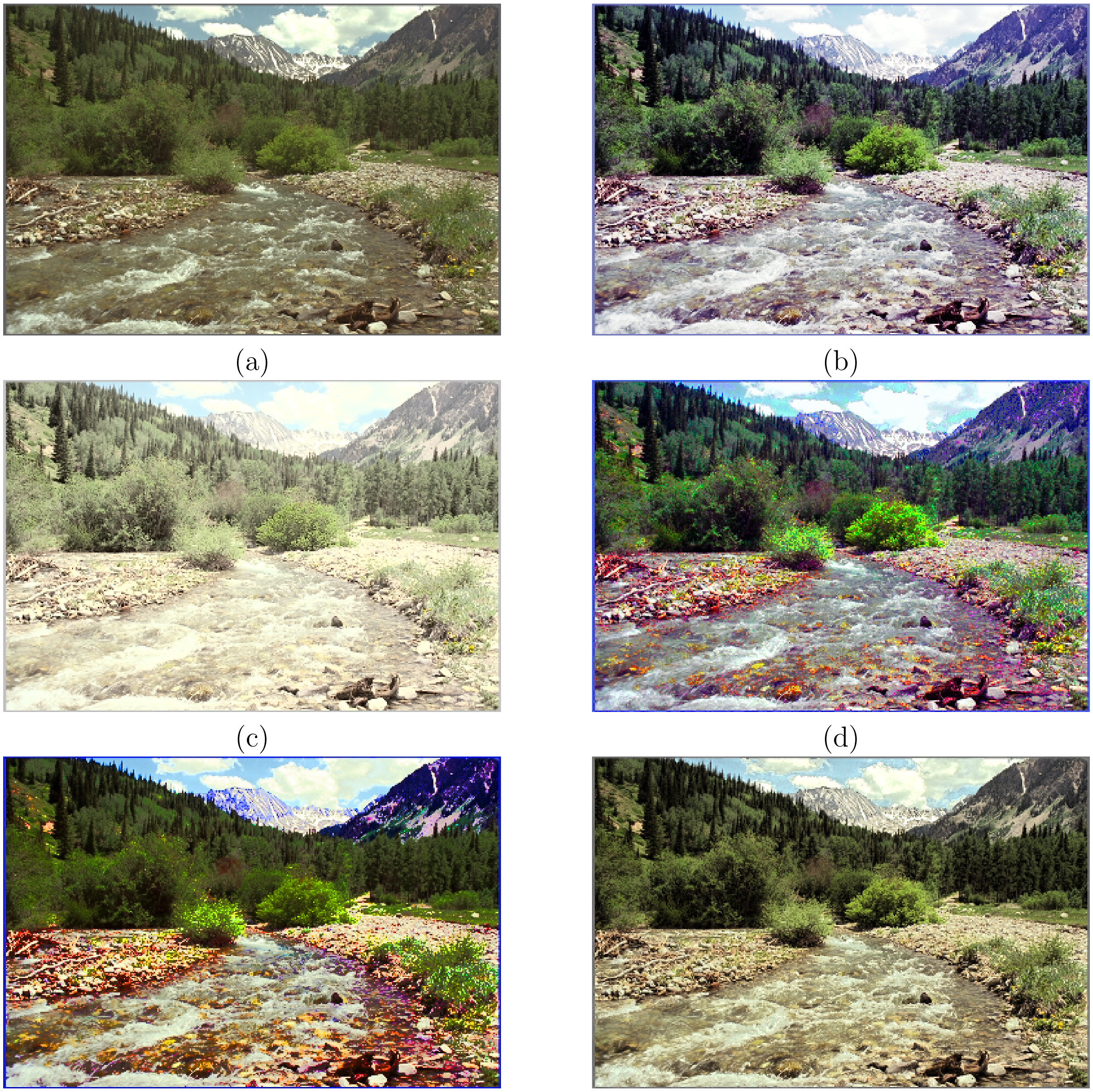
(e)

(f)

Figure 3: Results of histogram equalization: (a) The original 256×384 pixel “03” image. (b) The image after histogram equalization on each channel independently. (c) The image after 3-D histogram equalization. (d) The image after histogram decimation. (e) The image after histogram explosion. (f) The image after ANHE with $N_{max} = 100$, $N_{min} = 20$, $T = 20$, and $\kappa = 3$.

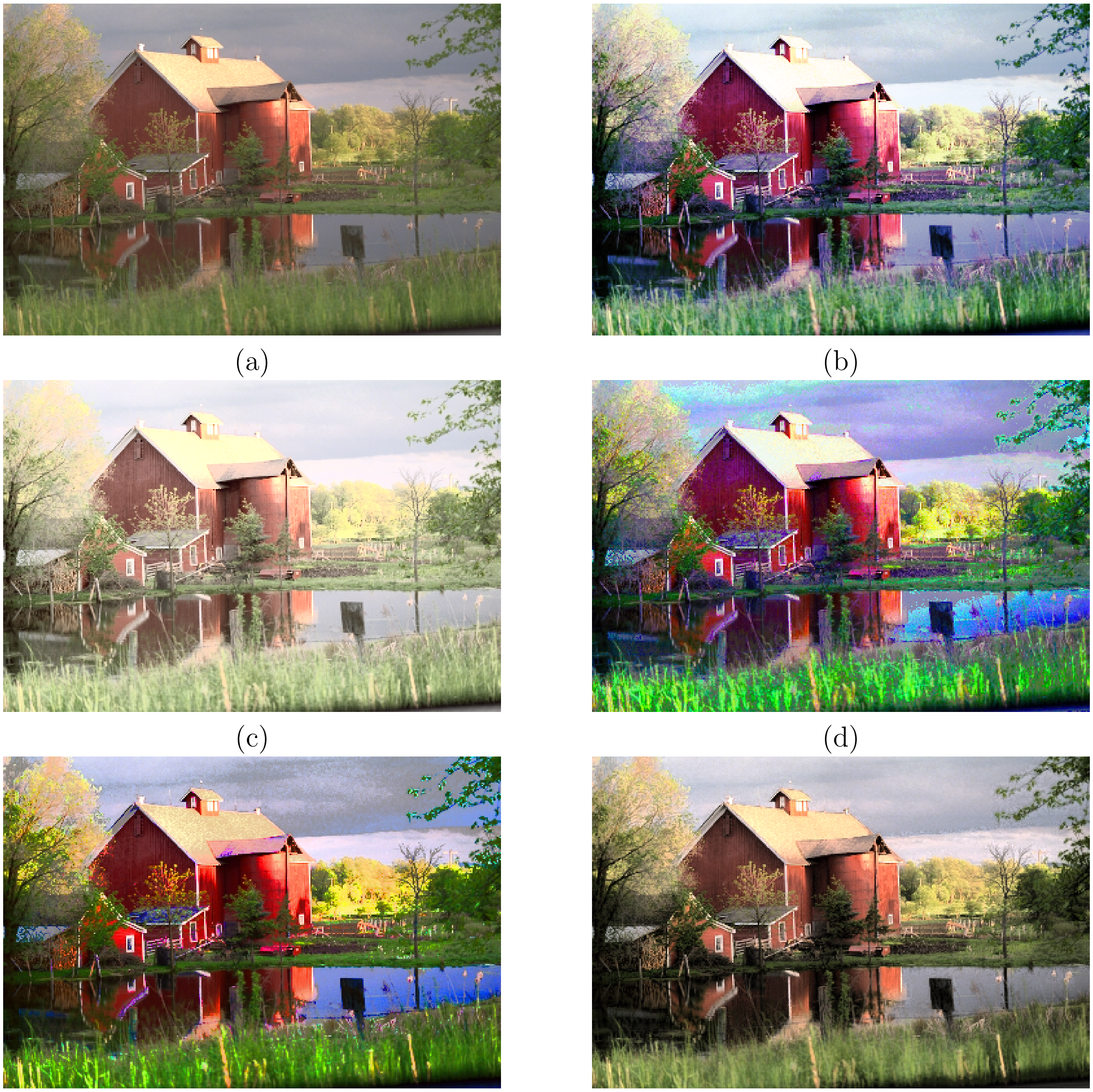
(a) (b) (c) (d) (e) (f)

Figure 4: Results of histogram equalization: (a) The original 256×384 pixel "08" image. (b) The image after histogram equalization on each channel independently. (c) The image after 3-D histogram equalization. (d) The image after histogram decimation. (e) The image after histogram explosion. (f) The image after ANHE with $N_{max} = 100$, $N_{min} = 20$, $T = 20$, and $\kappa = 3$.



(a) (b) (c) (d) (e) (f)

Figure 5: Results of histogram equalization: (a) The original 256×384 pixel "13" image. (b) The image after histogram equalization on each channel independently. (c) The image after 3-D histogram equalization. (d) The image after histogram decimation. (e) The image after histogram explosion. (f) The image after ANHE with $N_{max} = 100$, $N_{min} = 20$, $T = 20$, and $\kappa = 3$.



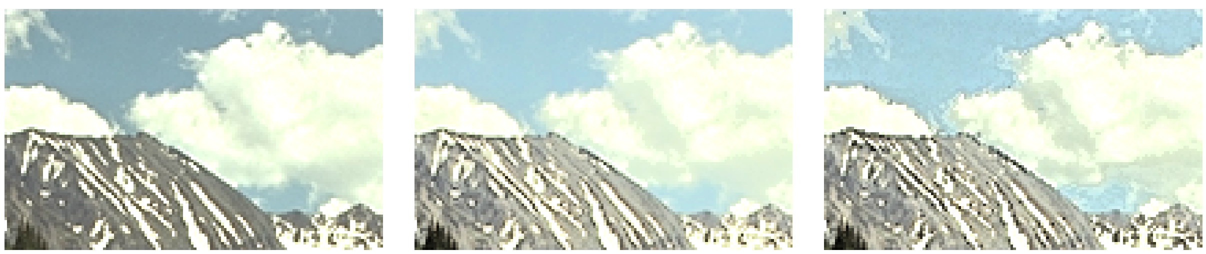
(a) (b) (c) (d) (e) (f)

Figure 6: Results of histogram equalization: (a) The original 256×384 pixel "22" image. (b) The image after histogram equalization on each channel independently. (c) The image after 3-D histogram equalization. (d) The image after histogram decimation. (e) The image after histogram explosion. (f) The image after ANHE with $N_{max} = 100$, $N_{min} = 20$, $T = 20$, and $\kappa = 3$.

Figure 7: Results of ANHE: (a) Original "01" image (b) "01" image after ANHE (c) Original "05" image (d) "05" image after ANHE (e) Original "06" image (f) "06" image after ANHE

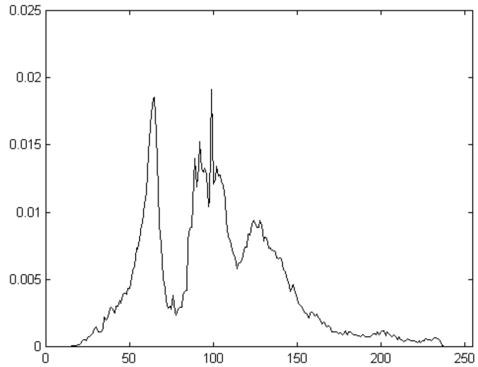
(a) (b) (c) (d) (e) (f)

Figure 8: Results of ANHE: (a) Original “07” image (b) “07” image after ANHE (c) Original “14” image (d) “14” image after ANHE (e) Original “23” image (f) “23” image after ANHE

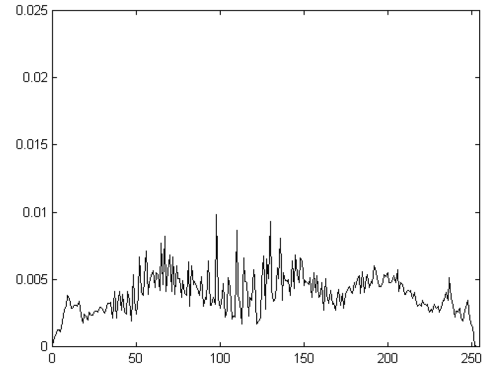


(a) (b) (c)

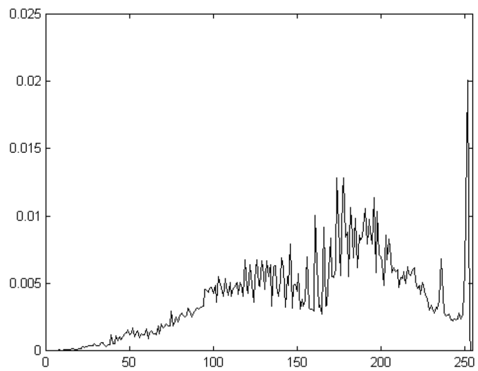
Figure 9: Detail emphasis by ANHE: (a) 88×138-pixel portion of the original “13” image. (b) Same portion of the image after histogram equalization of brightness only. (c) Image after ANHE.



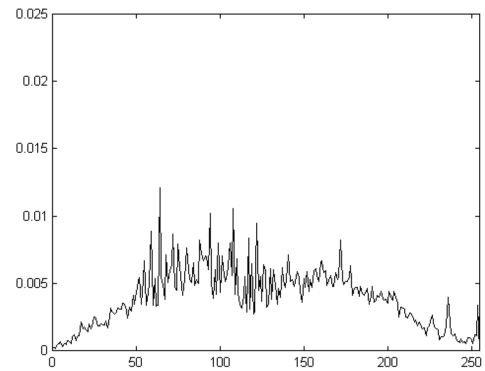
(a)



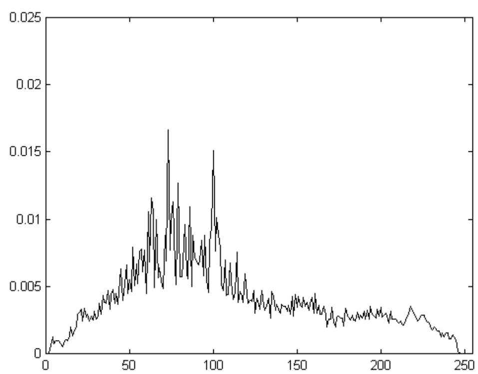
(b)



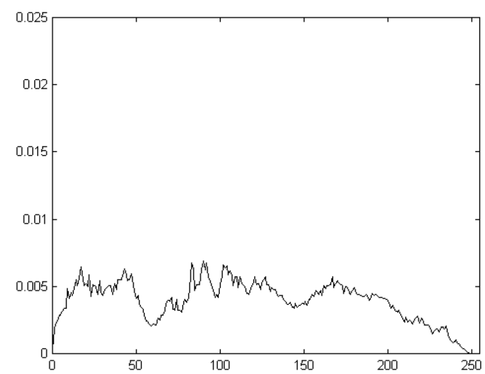
(c)



(d)



(e)



(f)

Figure 10: Histograms of intensities of the images in Figure 3: (a) Original. (b) After histogram equalization on each channel independently. (c) After 3-D histogram equalization. (d) After histogram decimation. (e) After histogram explosion. (f) After ANHE.