A New Method for Image Contrast Enhancement Based on Automatic Specification of Local Histograms

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Summary

The histogram equalization (HE) method is widely used for image contrast enhancement. While it can enhance the overall contrast, the inherent dependence of its transformation function on the global content of the image limits its ability to enhance local details at the same time. Furthermore, using the method to reform the image histogram into a uniform one usually results in a significant change in the image brightness and saturation artifacts, specifically in low contrast images. One extension for HE is the local histogram equalization (LHE) method that processes the image on block-by-block basis and uses the transformation function of HE for that block to modify its center pixel. Although the LHE method can enhance image details, it often causes unacceptable and unnatural image modification due to noise amplification, especially in smooth regions. In this paper, we propose a new local enhancement method referred as Automatic Local Histogram Specification (ALHS). The ALHS method is applied locally such that for each pixel in the image a neighborhood/block of specific size is defined with that pixel being at the center of the block. Next, the ALHS method modifies the graylevel value of this central pixel by specifying an output histogram and applying the histogram matching algorithm. The core idea of the ALHS method is specifying the best output histogram for the block associated with each pixel. To specify the output histogram, a minimization problem for a functional with a constraint that preserves the mean brightness of that block is solved. The specified histogram in the ALHS method provides the maximum graylevel stretching and preserves the mean brightness of the block. This is reflected on the processed image by the enhancement of its contrast, preservation of its outlook, and minimum introduction of noise and overenhancement artifacts. The ALHS method is fully automatic and provides an analytic solution for the output histogram as a function of the mean brightness of the block. Our experimental evaluation on a set of benchmark images involved the use of two quantitative measures and visual assessment. The evaluation results show that the ALHS method outperforms both the HE and LHE methods.

Key words:

Contrast, entropy, histogram equalization, histogram matching.

1. Introduction

The purpose of image contrast enhancement methods is to increase image visibility and details. Numerous enhancement methods have been proposed in the literature. This primarily includes: histogram processing methods [1]–[11], graylevel compression and stretching using exponentials and polynomials [1,2,12], spatial statistical filtering [13,14,15], and frequency domain processing techniques [16,17]. The enhancement efficiency, computational requirements, noise amplification, user intervention, and application suitability are the common factors to be considered when choosing from these different methods for specific image processing application. The histogram equalization (HE) method is probably one of the most known contrast enhancement methods for graylevel images due to its simplicity and effectiveness [1]-[4]. In principle, the histogram equalization method increases the contrast of the image by transforming its histogram into a uniform one that spans the full graylevel range. This is based on the assumption that for maximum transfer of information, the perceived distribution (histogram) of graylevels in an image should be uniform. It can be easily shown that the for discrete 8-bit grayscale images, the HE method achieves this by using the transformation function

$$s = T(r) = 255 \times \sum_{w=0}^{r} h_i(w)\, dw = 255 \times CDF(r),\ r \in [0,255] \qquad (1)$$

which is simply the cumulative distribution function $CDF(r)$ of the normalized original image histogram $h_i(r)$ [1,2].

Despite the simplicity and the implied definition of the transformation function in the histogram equalization method, there are some problems associated with it. First, the histogram equalization method results in a significant change of the mean brightness of the image. This is because the histogram equalization method reforms the original image histogram into a uniform distribution which has a mean at the middle of the graylevel range regardless of the original mean brightness value. Consequently, this may distort the original image outlook, especially for low contrast images. Second, the HE method may result in overenhancement and saturation artifacts due to the stretching of the graylevels over the full graylevel range. Third, the HE transformation function is capable of improving the global contrast of the image and may or

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may not increase the local contrast since it is based on the global content of the image. The problem of mean brightness change in the histogram equalization method has been addressed in [6]-[10]. Generally, these methods operate by dividing the graylevel range into two or more sections using some threshold values, and then they equalize each section independently using the histogram equalization method. Although they are proven to preserve the mean brightness to some extent, they are applied globally and they are still based on the original histogram equalization method, which means they may produce overenhancement and saturation artifacts within each graylevel section. To extend the method of histogram equalization for local enhancement, adaptive or local histogram equalization (LHE) was proposed [4,11,18]. In the LHE method, each pixel in the image is modified by initially defining a rectangular block of specific size in its neighborhood, such that the pixel is at the center of the block. Afterwards, the HE transformation function of that block is used to change the center pixel. This operation is repeated for all the pixels in the image by moving the center of the block. This extension of histogram equalization allows each pixel to adapt to its neighborhood, so that high contrast can be obtained for all locations in the image. However, the LHE method usually results in an unnatural modification in the processed image due to excessive noise amplification, especially in smooth regions. Also, the LHE method produces edge artifacts at sharp boundary points where the local transformation changes abruptly due to rapid change of the local histogram [19]. This is because the LHE method is only the local extension of the HE method, thus it inherits its overenhancement and saturation problems that mainly result from the absence of a limit on the amount of stretching of the graylevel values.

The histogram matching (HM) is another method for contrast enhancement. In this approach, the contrast of the original image is modified by specifying the histogram of the desired image. Actually, the histogram equalization method can be viewed as a special case of histogram matching with the desired histogram being the uniform distribution. After the specification of the desired histogram, the original histogram is transformed to the desired one using the approach detailed in [1,2]. In this approach, each input graylevel r is mapped to the output graylevel s such that the difference between the corresponding values of the input and output cumulative distribution functions is minimized. In other words, for each r we are looking to find a s such that

$$s = \arg\min_{s \in [0,L]} \left| T(r) - G(s) \right| \qquad (2)$$

where $T(r)$ and $G(s)$ are the cumulative distribution functions of the input and desired histograms, respectively, and L is the maximum available graylevel. Histogram matching is a powerful technique but with one major inherent issue; how to define the desired histogram? This is usually application dependent and requires user involvement which renders the HM method inefficient for automatic contrast enhancement.

In this paper we propose a new method; Automatic Local Histogram Specification (ALHS), that automatically provides the optimal contrast enhancement with minimal distortion in the image appearance. Basically, the ALHE method is applied locally just like the LHE method. However, to modify the pixel at the center of the block, a desired output histogram for that block is specified then the histogram matching algorithm (HM) [1,2] is used to find the new value of the pixel. The core idea in the ALHS method is the specification of the desired histogram for each block. The ALHS method automatically defines this histogram such that it is the closest to the uniform distribution as in the HE method, and at the same time has a mean brightness with minimum deviation from the mean brightness of the original block. These requirements are formulated into a mathematical optimization problem whose solution specifies the desired histogram in an analytic expression that is a function of the block original mean brightness. The rationale behind this approach is that preserving the mean brightness of the block when modifying central pixels enhances the image contrast, preserves its global outlook, and minimizes the introduction of noise and overenhancement artifacts The ALHS method was compared to the HE and LHE methods by processing a set of benchmark images and using visual assessment and two quantitative measures. The evaluation results proved the ALHS method to be better than the HE and LHE methods.

The rest of this paper is organized as follows. In Section 2, we study the formulation of the objective function in the ALHS method and its solution. Section 3 presents some experimental results and section 4 concludes the paper.

2. The ALHS Method

The enhancement of image quality is tricky in the sense that it should require minimum user involvement and improve the image details without modifying its outlook and introducing artifacts. According to the discussion in the introduction section, this is not achievable using the HE or HM methods separately. However, it sounds intuitive to use the principles from both methods to design a proper enhancement method. This is the basic idea for our method, the Automatic Local Histogram Specification (ALHS), where we first exploit the idea of the histogram equalization method to automatically specify the desired block histogram $h_d(s)$ that would preserve the block original mean at each pixel in the image, and then we apply the histogram matching to perform the required graylevel transformation. In the following two subsections we will discuss the details of the ALHS method.

2.1 Specifying the Desired Block Histogram $h_d(s)$

The specified histogram for the image blocks should have comparable enhancement capabilities as the HE and LHE methods and at the same time preserves the visual quality of the original image. Accordingly, we propose that the desired block histogram should be as close as possible to the uniform distribution but with mean value that is equal to block original mean. We claim that this approach will result in a histogram that is able to limit the amount of graylevel stretching, thus it will able to reduce the overenhancement artifacts and noise amplification while enhancing the image contrast and details. Mathematically, let's assume that the input and output graylevels, r and s, respectively, can be represented as continuous random variables that have been normalized, i.e. $0 \le r, s \le 1$. Then, the desired block histogram should have the following properties: (i) the mean or the expected value of the desired block histogram μ_d is equal the original block mean brightness μ_o, that is

$$\mu_d = \int_0^1 s\, h_d(s)\, ds = \mu_o \qquad (3)$$

(ii) The total difference between the desired block histogram $h_d(s)$ and the uniform distribution

$$h_u(s) = 1\ ,\ \forall\, s \in [0,1] \qquad (4)$$

is minimum. In other words, the expression

$$\int_0^1 (h_d(s) - h_u(s))^2\, ds \qquad (5)$$

should be minimized. (iii) The desired block histogram should satisfy the two basic properties of the probability density functions, which are

$$h_d(s) \ge 0\ ,\ \forall\, s \in [0,1] \qquad (6)$$

$$\int_0^1 h_d(s)\, ds = 1 \qquad (7)$$

Accordingly, we formulate the following objective function

$$J(h_d(s)) = \int_0^1 (h_d(s) - h_u(s))^2\, ds + \lambda_1 \left[\int_0^1 h_d(s)\, ds - 1 \right] + \lambda_2 \left[\int_0^1 s\, h_d(s)\, ds - \mu_o \right] \qquad (8)$$

with λ_1 and λ_2 being the Lagrange multipliers associated with the constraints in (7) and (3), respectively. The optimal desired block histogram $h_d(s)$ is the one that minimizes the functional $J(h_d(s))$ defined in (8). This can be solved directly using the calculus of variations; however, the global point-wise inequality constraint in (6) makes the direct use of the Euler-Lagrange multiplier theorem inapplicable. Instead, we have to use the principle of the slack functions [21], which starts by finding the optimal solution of the objective function without considering the inequality constraint, and then it checks if this solution satisfies that constraint. If this is the case, then no further actions are required and the solution represents the desired block histogram that we are looking for. On the other hand, if the inequality constraint is not satisfied by the given solution, a special procedure is followed to define a composite extremum curve consisting of pieces of arcs along which the usual Euler-Lagrange equation holds and pieces of arcs along which the inequality constraint holds. Based on this, let's first ignore the inequality constraint and use the calculus of variations and the Euler-Lagrange equation

$$J_{h_d} - \frac{d}{dr}(J_{h'_d}) = 0 \qquad (9)$$

to minimize the functional in (8). The term J_{h_d} is the partial derivative of J with respect to h_d. Similarly, $J_{h'_d}$ is the partial derivative of J with respect to the first derivative of h_d. Accordingly, we obtain the general solution for $h_d(s)$ to be

$$h_d(s) = 1 - 0.5(\lambda_1 - \lambda_2 s)\ ,\ s \in [0,1] \qquad (10)$$

Next, applying the constraints in (3) and (7) to (10), we can find the values for λ_1 and λ_2 and define the desired block histogram as

$$h_d(s) = 1 + 6(\mu_o - 0.5)(2s-1)\ ,\ s \in [0,1] \qquad (11)$$

Next, we have to check if this expression is positive, i.e. satisfies the inequality in (6), over the full graylevel range [0,1] and for all possible values of original block mean brightness μ_o. This can be done easily by some mathematical manipulation where we solve for the values of μ_o that would make (10) less than zero. Unfortunately, this manipulation reveals that the specified histogram in (10) violates the inequality in (6) when the original block mean μ_o is in the range of (0,1/3) or (2/3,1). Let's refer to these two cases as *Case 1* and *Case 3*, respectively. On the other hand, when μ_o falls in the interval [1/3,2/3] (call it *Case 2*), the solution for the desired histogram is always positive in the range [0,1], thus the inequality is not violated. Figure 1 demonstrates how part of the desired block histogram is negative for *Case 1* and *Case 3*, but it is not for *Case 2*. Consequently, we have to find the solution for *Case 1* and *Case 3* as a composite curve that would clip the negative portion of the desired histogram to zero. Based on Figure 1, the composite desired histogram in *Case 1* will be defined as defined as

$$y_1(s) = \begin{cases} h_d(s) & , 0 \le s \le \delta \\ 0 & , s \ge \delta \end{cases} \quad (12)$$

Similarly, the desired histogram in *Case 2* is given by

$$y_2(s) = \begin{cases} 0 & , 0 \le s \le \theta \\ h_d(s) & , s \ge \theta \end{cases} \quad (13)$$

with δ and θ being the cutoff point between the two portions of the composite curves. The values of these two constants will be found based on the constraints in (3) and (7) once the solution is found. Now, according to the Lagrange multiplier theorem, at least the following condition

$$\delta J(h_d(s), \square h_d(s)) = \sum_i \lambda_i \delta K_i(h_d(s), \square h_d(s)) \quad (14)$$

has to be satisfied for an extremum to exist, with δJ and δK_i are the variations for the functional J and the i[th] constraint K_i, respectively. So, we can now solve for the desired block histogram in *Case 1* and *Case 3* separately by plugging the definitions of the composite histograms for *Case 1* and *Case 3* in (14) and using the definition of the variation

$$\delta F(h_d(s), \square h_d(s)) = \frac{d}{d\varepsilon} F(h_d(s), \varepsilon \square h_d(s)) \Big|_{\varepsilon=0} \quad (15)$$

for any functional F. Accordingly, the general shape of the desired block histogram in both cases will be

$$h_d(s) = 1 + 0.5(\lambda_1 + \lambda_2 s) \quad (16)$$

over the interval $[0,\delta]$ and $[\theta,1]$ in *Case 1* and *Case 3*, respectively. Next, if apply the constraints in (3) and (7) over the specified interval in each case, we get the expression for the desired block histogram in for *Case 1* and *Case 3* as listed in Table 1 (the reader is encouraged to check [21] for more details). As a result, given any normalized value for the block mean brightness falling in the range (0,1), we can now automatically provide a mathematical expression for the desired block histogram in the ALHS method. For the case when the block contains only one graylevel (this includes the cases when the mean brightness is 0 or 1), it is obvious that the pixel value at the center of the block should not be changed in order to preserve the original mean value. This implies the desired block histogram $h_d(s)$ would be the original block histogram $h_o(s)$ as shown in *Case 4* of Table 1.

The desired block histogram in the ALHS method is a straight line segment that either covers the entire domain, $s \in [0,1]$, as in case 2, or part of it as in cases 1 and 3. If the mean block brightness is equal to 0.5, the desired block histogram reduces to a uniform distribution as in the histogram equalization method. The parameter δ in *Case 1* and θ in *Case 3* determine the cut-off point after (or before for *Case 3*) which the desired histogram $h_d(s)$ is clipped to zero. This situation happens because the mean of the input block is too low (*Case 1*) or too high (*Case 3*) to spread the original histogram of the block over the entire graylevel. This clipping property of ALHS and the dependence of the desired histogram on the original mean value enable the ALHS method to preserve the block mean brightness and reduce the amount of stretching. This is reflected on the output image by minimum change in its appearance and reduced noise amplification and overenhancement artifacts.

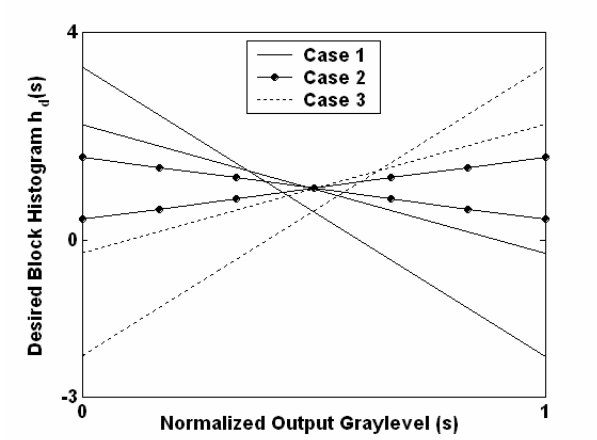

Figure 1. The shape of the desired block histogram for different values of μ_o.

2.2. Digitization and Histogram Matching

The derivation of the desired block histogram in the previous section was under the assumption that the output domain s is a continuous random variable. However, this is not true for digital images. Thus, it is necessary to digitize the specified histogram before we proceed to the histogram matching step. This can be achieved using one of the methods described in [22]. In our implementation, we used the Equal Width Interval approach to digitize the s domain into 256 discrete levels (number of levels in 8-bit grayscale images).

Once the discrete version of the desired histogram for the block is available, the histogram matching algorithm is carried out to define the transformation function that is to be used to modify the value of the pixel at the block center. However, the algorithm discussed in [1,2] requires that the cumulative distribution function of the desired histogram to be strictly monotonically increasing to avoid one-to-multiple graylevel mappings. Apparently, the histograms specified in *Case 1* and *Case 3* violate this requirement. Accordingly, we have modified the original histogram matching algorithm intuitively such that for any input graylevel r^* that could be mapped to more than one graylevel, it is mapped using one of the four rules listed in Table II, where s^* represents the output graylevel. We

Table 1. The mathematical expressions of the desired histogram for the three different cases in the in ALHS method based on the original block mean u_o.

Case No.	Condition	Desired Block Histogram
1	$u_o \in (0, 1/3)$	$h_d(s) = \begin{cases} -2\delta^{-2}(s-\delta), & s \le \delta \\ 0, & otherwise \end{cases}$ where $\delta = 3\,\mu_o$
2	$u_o \in [1/3, 2/3]$	$h_d(s) = 1 + 6(\mu_o - 0.5)(2s-1)$, $s \in [0,1]$
3	$u_o \in (2/3, 1)$	$h_d(s) = \begin{cases} 0, & s \le \theta \\ 2(\theta-1)^{-2}(s-\theta), & otherwise \end{cases}$ where $\theta = 3\,\mu_o - 2$
4	$u_o = \{0,1\}$ *or the block contains a single graylevel*	$h_d(s) = h_o(r), \forall\, r = s$

Table 2. Rules added to the histogram matching algorithm to solve the problem of one-to-multiple mappings.

Case No.	Rule No.	Rule
1	I	*If* $\mathbf{r}^* \le \boldsymbol{\delta}$ *then* $\mathbf{s}^* = \boldsymbol{\delta}$
	II	*If* $\mathbf{r}^* > \boldsymbol{\delta}$ *then* $\mathbf{s}^* = \mathbf{r}^*$
3	III	*If* $\mathbf{r}^* \le \boldsymbol{\theta}$ *then* $\mathbf{s}^* = \mathbf{r}^*$
	IV	*If* $\mathbf{r}^* > \boldsymbol{\theta}$ *then* $\mathbf{s}^* = \boldsymbol{\theta}$

chose these rules such that overstretching and compression of graylevels is avoided. The only concern here is how these modifications will affect the performance of the ALHS method in preserving the appearance of the image? Actually, the pixel count of such levels compromise a small percentage in low contrast images, especially when operating at the pixel level, so even if they are mapped to the cutoff point (rules I and IV) or kept unchanged (rule II and III), their effect will be minimal and may not be detected by the human eye.

3. Experimental Evaluation

In this section we present some simulation results for the proposed ALHS method and compare it to the HE and LHE methods in terms of the level of contrast enhancement and the preservation of the original image appearance. The comparison between the three methods is done through the use of two quantitative measures supplemented with visual inspection. The first measure is the Absolute Mean Brightness Error, which is defined as

$$AMBE = |\,\mu_p - \mu_o\,| \qquad (17)$$

and it simply measures the deviation of the processed image mean μ_p from the input image mean. The AMBE provides a sense of how the image global appearance has changed, with preference to lower values [9]. The second measure that we used is the discrete entropy H,

$$H = \sum_{s=0}^{255} h(s)\log_2 h(s)\ ,\ \forall h(s) \ne 0 \qquad (18)$$

where $h(s)$ is the global normalized histogram of the processed image. Entropy has been used to measure the content of the image [23], with higher values indicating images that are richer in details. In addition to these two measures, we have also compared the three methods in terms of processing time requirements.

Our evaluation involved the processing of a large set of images obtained from [24] using a 1.3 GHz Pentium ® 4 processor with 1 GB memory. Three representative examples for the images: *Airport*, *Village,* and *Pirate* are shown in Figures 2-4. The size of these images is 512 x 512 pixels and the block size used in the implementation of the LHE and ALHS methods was 100 x 100 pixels.

Visual assessment of the processed images showed that the ALHS method has the ability of enhancing both the global and local details in the image better than the HE method with negligible saturation and overenhancement problems. When compared to the LHE method, the new method performed in a comparable fashion in terms of enhancing the details, but with the advantage of lower noise amplification. Also, it is clear from the results that the ALHS method resulted in a minimum change in the image outlook. Let's take for example the processing results for the *Airport* image. The HE method resulted in saturation and overenhancement in the planes and the top of the buildings and thus reduced the smaller details in these regions. In the LHS method, the local details are better than the HE method in these regions, however, the processed image looks unnatural due to noise amplification in the background. These problems were less pronounced in the ALHS method where we can see the enhanced details on the top of the buildings with reduced noise amplification in the background. Also, the ALHS method did not modify the global outlook of the image like the HE and LHE methods.

The visual assessment is supported by the computed AMBE and entropy values listed in Tables 3 and 4. Side by side comparison of the AMBE values for the three methods revealed that the ALHS method always outperformed both the HE method and the LHE method by having the lowest AMBE values. This is easily justified by the fact that ALHS modifies the block central pixel with the transformation function that would preserve the block mean if it is applied to the entire block, and effectively this helps preserving the general outlook of the image. The ALHS method is theoretically supposed to produce zero AMBE values when used in the continuous domain. This was not the case in our discrete domain study here which involves quantization errors. For the entropy values, the ALHS method increased the image content better than HE. Actually, the entropy values for the HE method are always less than the original value, because as we said earlier the HE method is global and thus results in reduction in the details. Comparing the ALHS method to the LHE method we see that the ALHS method has slightly *lower* values. This is because the ALHS method constrains the enhancement to avoid overstretching and noise amplification for the sake of preserving the image appearance. However, combining the visual assessment for the ALHS method with its AMBE and entropy values definitely makes it better than the LHE method that has higher entropy but degraded image outlook. In summary, we can say that the ALHS method outperforms the HE and LHE methods in enhancing the quality of grayscale images. Specifically, it is better than the HE method in terms of enhancing the local details and preserving the image outlook with negligible saturation and overenhancement artifacts. Also, it is capable of enhancing local details in a similar manner to the LHE method but with lower levels of noise amplification.

In terms of processing time, the HE, LHE, and ALHS methods required on average 50 ms, 119 s, and 203 s, respectively to process the 512x512 images. It is apparent that the HE method has the least processing time. This is because it is applied in a global fashion, in contrast to the other two methods that are applied locally. The difference in processing time between the ALHS and LHE methods is due to the additional steps required in the ALHS method for histogram matching and discretization. Nonetheless, this should not be an issue in non real-time image processing applications that demand images with high quality.

Table 3. AMBE values for the processed images.

	Airport	**Village**	**Pirate**
ALHS-Processed Image	0.73	0.51	2.04
HE-Processed Image	55.58	14.23	16.88
LHE-Processed Image	55.64	16.79	18.65

Table 4. Discrete entropy values for the original and processed images.

	Airport	**Village**	**Pirate**
Original Image	4.73	5.18	7.24
ALHS-Processed Image	5.34	5.51	7.96
HE-Processed Image	4.62	5.05	7.14
LHE-Processed Image	5.53	5.53	7.98

4. Conclusion

We have developed a new method called Automatic Local Histogram Specification (ALHS) for local contrast enhancement of graylevel images. The method automatically specifies the desired histogram that provides the optimal enhancement and preserves the mean brightness of the block around each pixel in the image. The ALHS method is proven through simulation to provide enhancement results that balance well between details enhancement and the preservation of the original image appearance - an objective that is difficult to achieve using the histogram equalization or local histogram equalization methods.

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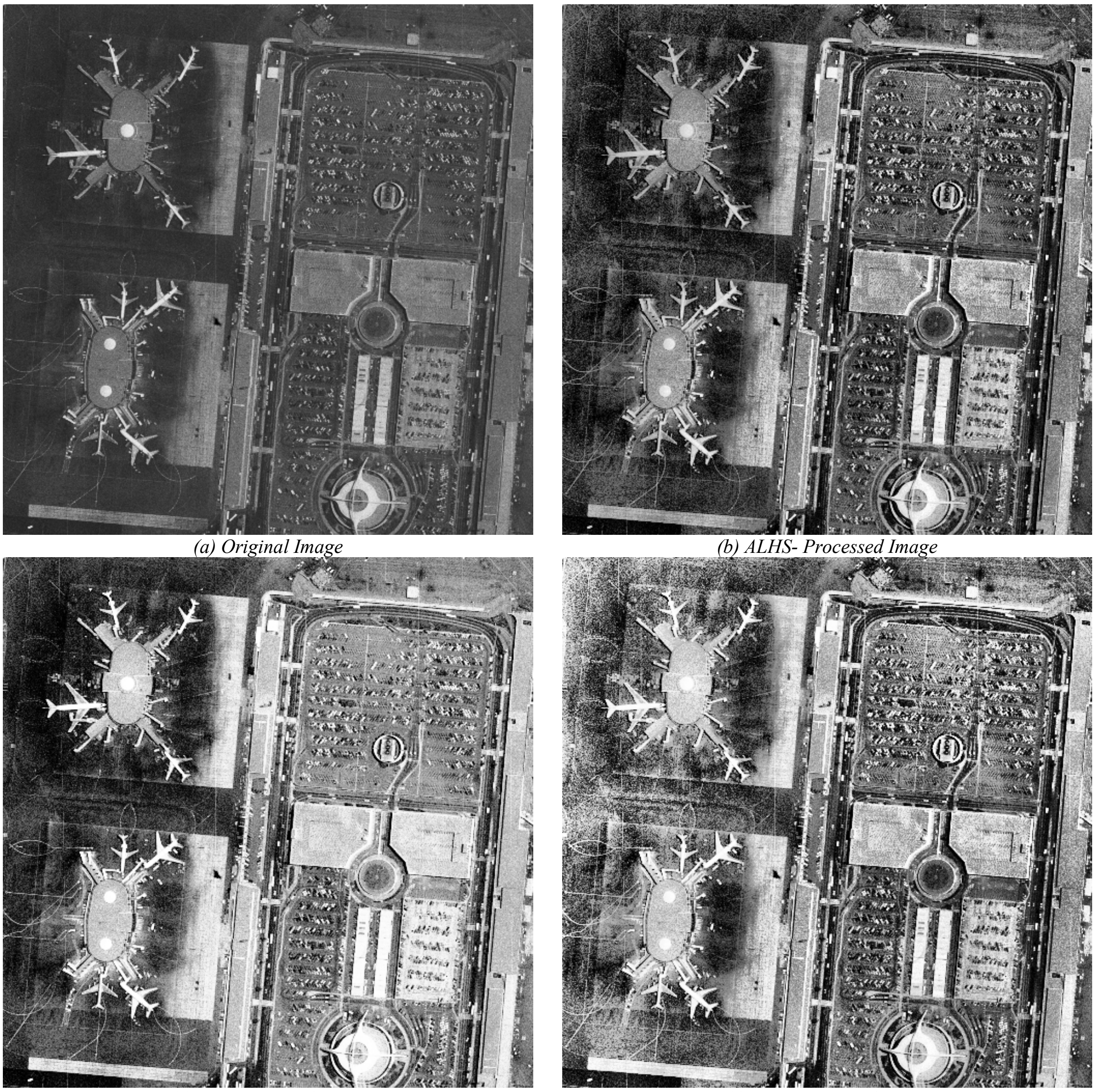

(a) Original Image *(b) ALHS- Processed Image*

(c) HE-Processed Image *(d) LHE-Processed Image*

Figure 2: Simulation results for image *Airport.*

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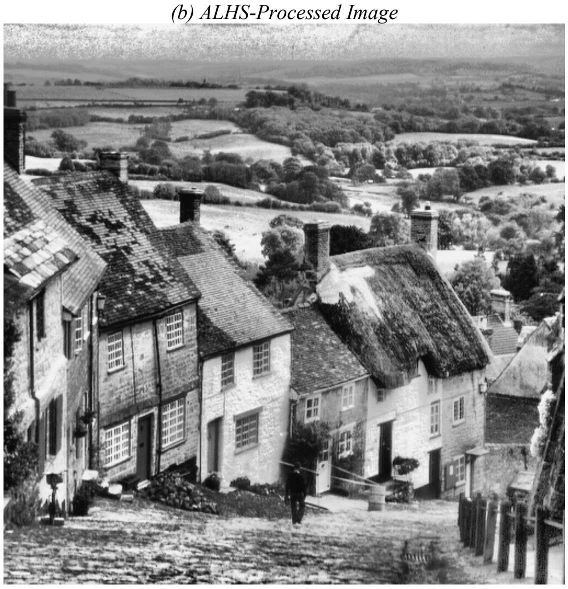
(a) Original Image

(b) ALHS-Processed Image

(c) HE-Processed Image



(d) LHE-Processed Image

Figure 3: Simulation results for image *Village.*

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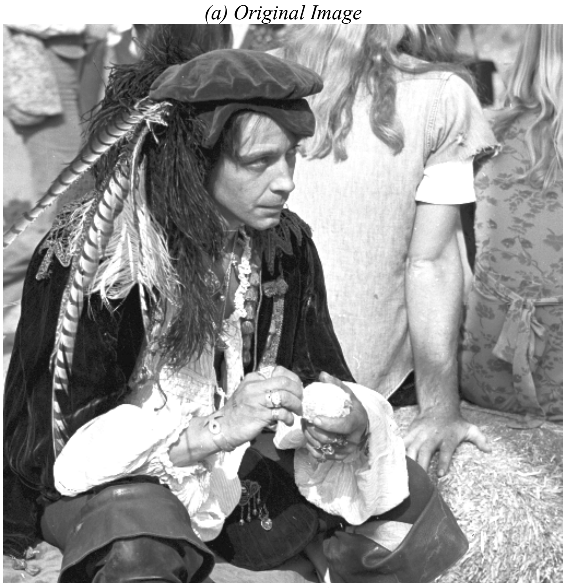
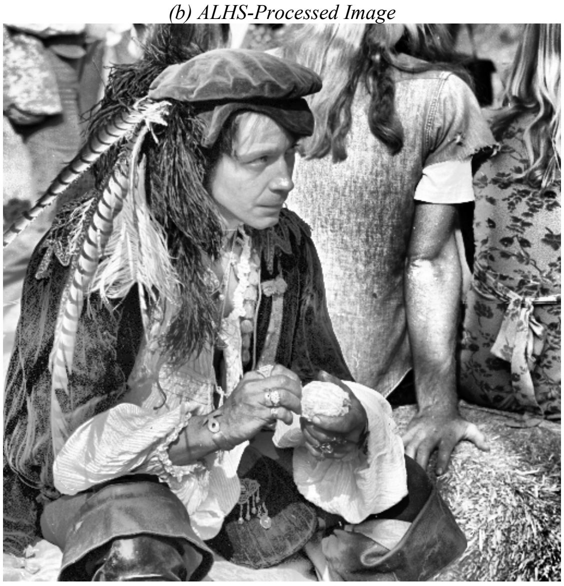
(a) Original Image

(b) ALHS-Processed Image



(c) HE-Processed Image



(d) LHE-Processed image

Figure 4: Simulation results for image *Pirate.*

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