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Research Article

Adaptive Inverse Hyperbolic Tangent Algorithm for Dynamic Contrast Adjustment in Displaying Scenes

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Contrast has a great influence on the quality of an image in human visual perception. A poorly illuminated environment can significantly affect the contrast ratio, producing an unexpected image. This paper proposes an Adaptive Inverse Hyperbolic Tangent (AIHT) algorithm to improve the display quality and contrast of a scene. Because digital cameras must maintain the shadow in a middle range of luminance that includes a main object such as a face, a gamma function is generally used for this purpose. However, this function has a severe weakness in that it decreases highlight contrast. To mitigate this problem, contrast enhancement algorithms have been designed to adjust contrast to tune human visual perception. The proposed AIHT determines the contrast levels of an original image as well as parameter space for different contrast types so that not only the original histogram shape features can be preserved, but also the contrast can be enhanced effectively. Experimental results show that the proposed algorithm is capable of enhancing the global contrast of the original image adaptively while extruding the details of objects simultaneously.

1. Introduction

Digital cameras, which have gradually replaced conventional cameras, store photographs in a digital format. However, this is not the only way in which digital cameras differ from conventional cameras. In conventional machinery cameras, the diaphragm and focal distance are adjusted by the photographer to obtain better scenes. Digital cameras, on the contrary, capture scenes using a sensor which might record a tremendous amount of energy from one material in a certain wavelength, while recording another material at much less energy in the same wavelength. Besides, the photographer cannot adjust the diaphragm or focal distance.

In real-world situations, light intensities have a large range. At the low end, the average intensity of starlight is approximately 10^{-3} cd/cm^2 and a sunny day can produce a high light intensity of 10^5 cd/cm^2 or more. However, the visible range perceived by the human eye is only 1 to 10^4 cd/cm^2. As a result, we lose almost all the details appearing in the darkest and brightest ranges of the visible spectrum. Today, most digital video cameras have the capability of capturing high dynamic range (HDR) images with a luminance level of 200% to 600%. Nevertheless, most display devices are only capable of a low dynamic range (LDR), with a luminance level of about 110% [1].

Visual adaptation in humans provides us with the ability to see in a wide range of conditions, from the darkness of night to the brightness of the midday sun. Adaptation means that the signals from our photoreceptors are processed to amplify weak signals and weaken strong signals, thereby preventing saturation. The previous physiological research shows that ganglion cells, the output cells of the retina, adapt at lower light levels than cones horizontal cells, one of the downstream targets of the cones [2]. This provides evidence for adaptation in the retinal circuitry and in the cone photoreceptors, known as receptor adaptation. As light levels increase, the main site of adaptation switches from the retinal circuitry to the cone photoreceptors.

We see light that enters the eye and falls on the retina. The retina has two types of photosensitive cells, both of which

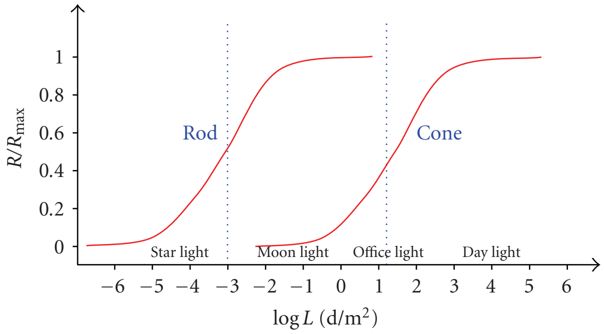


FIGURE 1: Human visual system mapping curve.

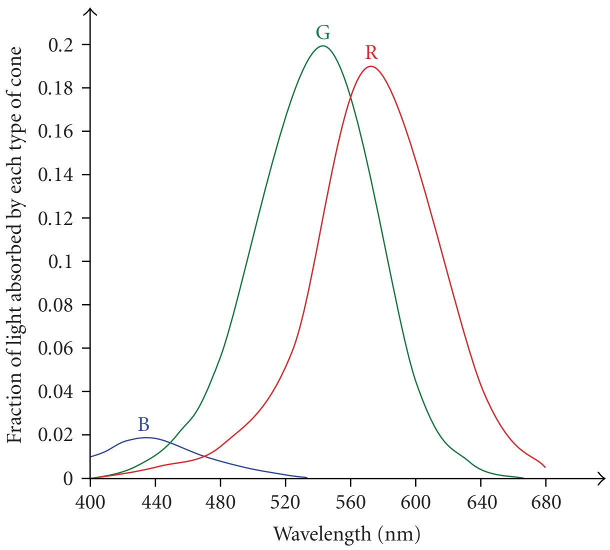


FIGURE 2: Sensitivity of the cones.

contain pigments that absorb visible light to give us the sense of vision. The rods, which are numerous, are spread all over the retina and respond only to light and dark. They are very sensitive and can respond to a single photon of light. There are about 110,000,000 to 125,000,000 rods in the eye [3]. The other type of cell is the cones located in one small area of the retina (the fovea). Their number is about 6,400,000. These cells are sensitive to colors but require more intense light in the order of hundreds of photons. Incidentally, the cones are very sensitive to red, green, and blue (Figures 1 and 2) [4, 5], which is the reason why monitors use these colors as primaries. There are three types of cones: A, B and, C cones. The A cones are sensitive to red light, and the B cones are sensitive to green light (slightly more than the A cones). The C cones are sensitive to blue light, but their sensitivity is about 1/30 that of the A or B cones.

The human eye features a much higher resolution than cameras but its effective resolution is even higher when we consider that the eye can move and refocus itself about three to four times a second. This means that in a single second the eye can sense and send to the brain about half a billion pixels.

The eye is a complex biological device. A camera is often compared to an eye because both focus the light from external objects in the visual field into a light-sensitive medium. In the case of the camera, this medium is film or an electronic sensor as opposed to the eye which is an array of visual receptors. According to the laws of optics, this simple geometrical similarity means that both eyes and a CCD camera function as transducers.

Light entering the eye is refracted as it passes through the cornea. It then passes through the pupil (controlled by the iris) and is further refracted by the lens. The cornea and lens act together as a compound lens to project an inverted image onto the retina.

A common problem in digital cameras is that the range of reflectance values collected by a sensor may not match the capabilities of the digital format or color display monitor. So, image enhancement techniques are generally required to make an image easier to analyze and interpret. The range of brightness values within an image is referred to as contrast. The contrast enhancement is a process that makes the image features stand out more clearly by optimizing the colors available on the display or an output device. A contrast enhancement algorithm allows users to custom design to improve image quality, representation, and interpretation.

Many factors contribute to image quality including brightness, contrast, noise, color reproduction, detail reproduction, visual acuity simulation, glare simulation, and artifacts. In so doing various digital images processing techniques have been developed. Among them is the contrast enhancement which plays the most important role in increasing the visual quality of an image [6, 7]. For this reason, the contrast enhancement has been the major approach to improve image quality.

According to image contrast an images is generally categorized into one of five groups: dark image, bright image, back-lighted image, low-contrast image, and high-contrast image. A dark image has particular low gray levels in intensity, while a bright image has very high gray levels in intensity. The gray levels of a back-lighted image are usually distributed at the two ends of dark and bright regions. On the other hand, the gray levels of a low-contrast image are generally centralized on the middle region, while the gray levels of a high-contrast image are scattered across the whole spectrum (Figure 3) [8].

Five categories of commonly used gray level transfer functions shown in Figure 4 are generally used to perform contrast enhancement so as to achieve different types of contrast [8]. For example, for dark images with mean <0.5, the function in Figure 4(a) is used; whereas the function in Figure 4(b) is used for a bright image with mean >0.5 for the same purpose. For images whose gray levels are centralized in the middle region with mean near at 0.5, the function in Figure 4(c) is used. For images whose gray levels are distributed at the two end of dark and bright region, the function in Figure 4(d) is used. For the images whose gray levels are uniformly scattered across the whole spectrum, the function in Figure 4(e) is used.

This paper presents an Adaptive Inverse Hyperbolic Tangent (AIHT) algorithm for image contrast enhancement

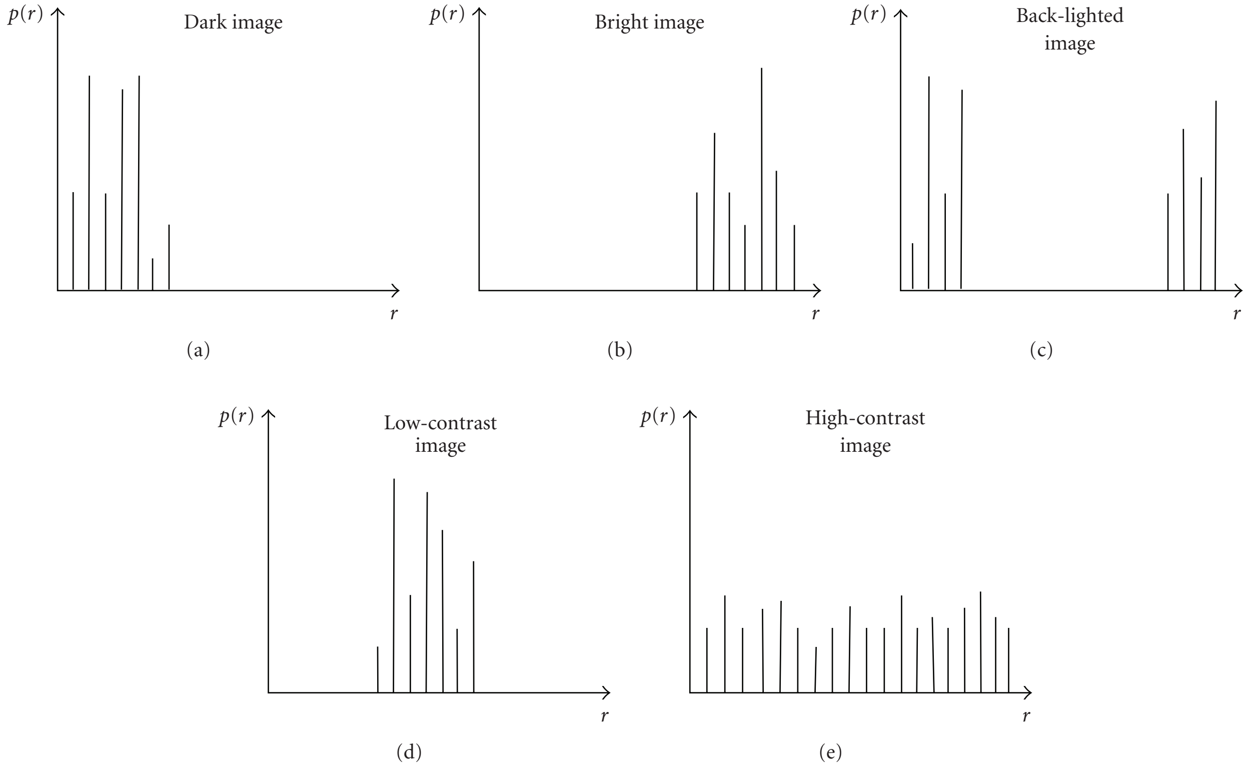


Figure 3: Five kinds of contrast types.

that is suitable for interactive applications. It can automatically produce contrast enhanced images with good quality while using a spatially uniform mapping function that is based on a simple brightness perception model to achieve better efficiency. In addition, the AIHT also provides users with a tool of tuning the on-the-fly image appearance in terms of brightness and contrast and thus is suitable for interactive applications. The AIHT-processed images can be reproduced within the capabilities of the display medium to have better detailed and faithful representations of original scenes.

The remainder of this paper is organized as follows. Section 2 reviews the previous work done in the literature. Section 3 develops the AIHT contrast enhancement algorithm along with its parameters and usage. Section 4 conducts experiments including simulations. Finally, Section 5 provides future directions of further research.

2. Contrast Enhancement for an Image

Each pixel in a gray-scaled image has brightness ranging from 0 to 255 with the values of 0 and 255 representing black and white, respectively. A histogram shows the number of pixels with the various levels of brightness. The "0" value on the left of a histogram shows the number of pixels that are black, while the "255" value on the right indicates the number of pixels being white. Normalizing the histogram by the total number of pixels in the image produces a probability distribution of brightness levels.

Since a digital image is encoded by L bits, the gray level of brightness varies from 0 to 2^{L-1}. Assume that r_k is the kth gray level. Its probability is defined by

$$P(r_k) = \frac{n_k}{N}, \tag{1}$$

where n_k is the number of pixels specified by r_k, and N is the total number of pixels in the image. If the histogram of an image has a narrow dynamic range, it will be a low-contrast image. In this case, different objects in the image will have their brightness in nearly the same gray level range which may cause difficulty in object identification, object classification, and image processing. Under such a circumstance the contrast enhancement is generally performed to expand gray level range to mitigate the problem. One popular technique to accomplish this task is histogram equalization in (Gonzalez and Woods [9]).

There are two categories of contrast enhancement techniques: global methods and local methods. The advantages of using a global method are its high efficiency and low computational load. The drawback of using a global operator is its inability in revealing image details of local luminance variation. On the contrary, the advantage of a local operator is its capability of revealing the details of luminance level information in an image at the expense of very high computational cost that may not be unsuitable for video applications without hardware realization. Two types of global contrast enhancement techniques, linear and nonlinear, are discussed as follows.

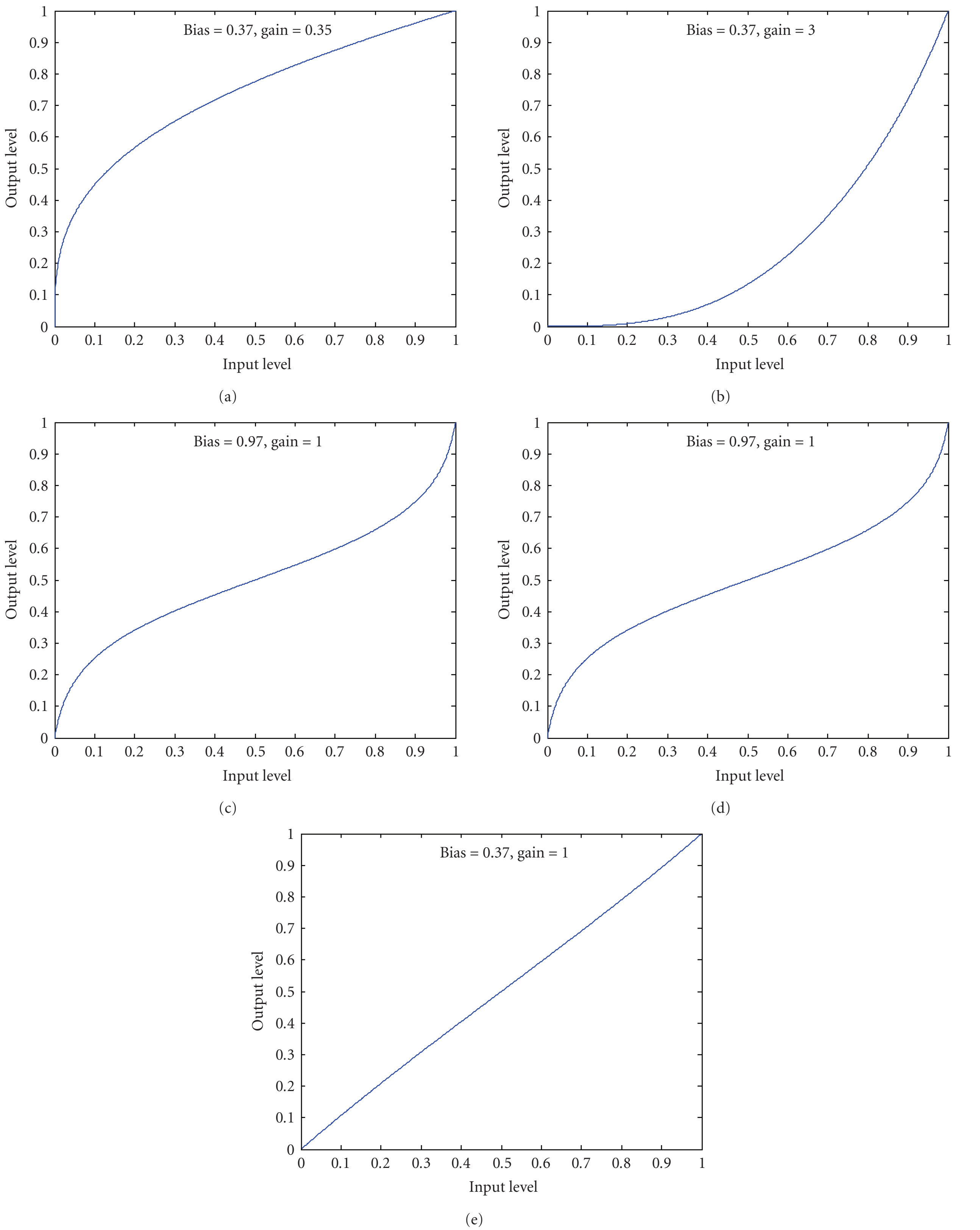


Figure 4: Five categories of commonly used gray level transform functions: (a) dark image, (b) bright image, (c) back-lighted image, (d) low-contrast image, and (e) high contrast image.

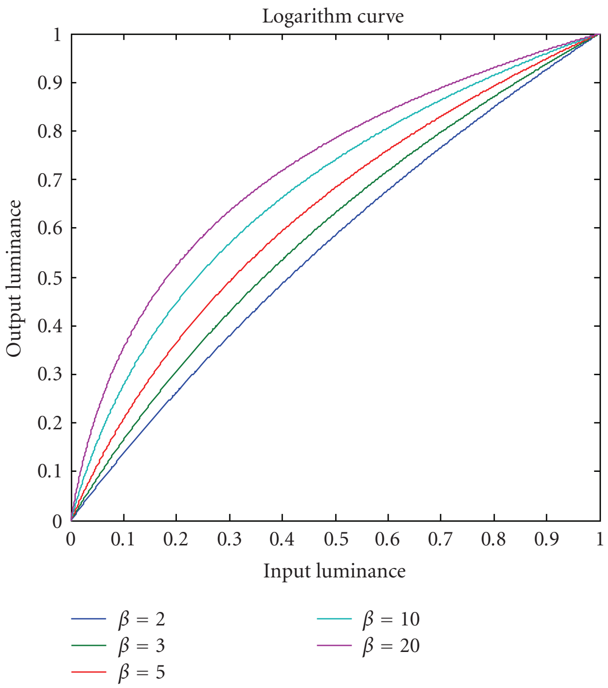


FIGURE 5: Logarithm curve for different β's value.

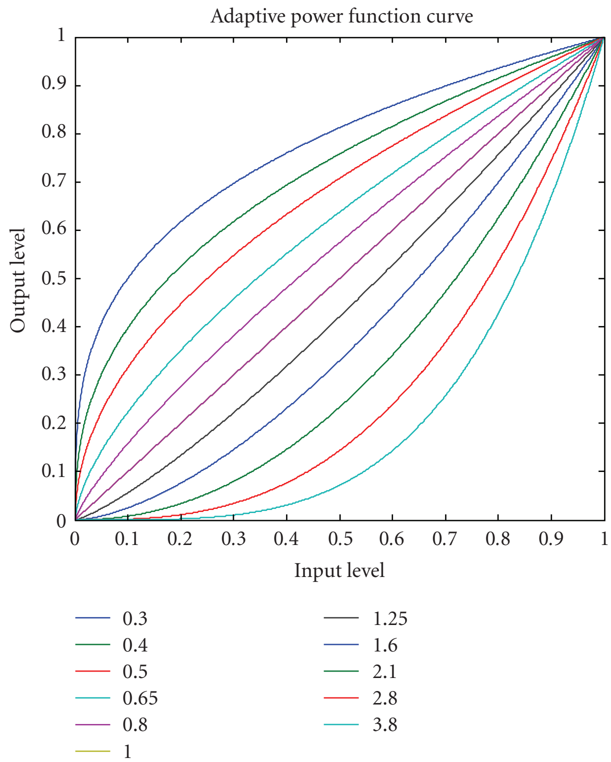


FIGURE 6: Gamma function curve for different γ's value.

2.1. Linear Contrast Enhancement. Linear contrast enhancement is also referred to as contrast stretching. It linearly expands the original digital luminance values of an image to a new distribution. Expanding the original input values of the image makes it possible to use the entire sensitivity range of the display device. Linear contrast enhancement also highlights subtle variations within the data. This type of enhancement is best suitable to remotely sensed images with Gaussian or near-Gaussian histograms. There are three methods of linear contrast enhancement.

2.1.1. Minimum-Maximum Linear Contrast Stretch. The minimum-maximum linear contrast stretch assigns the original minimum value to the new minimum value and the original maximum value to the new maximum value where the original intermediate values are scaled proportionately between the new minimum and maximum values. Many digital image processing systems can automatically expand these minimum and maximum values to optimize the full range of available brightness values.

2.1.2. Percentage Linear Contrast Stretch. The percentage linear contrast stretch technique is similar to the minimum-maximum linear contrast stretch except that the minimum and maximum values are found in a way that the values between them cover a given percentage of pixels from the mean of the histogram. A standard deviation from the mean is often used to push the tails of the histogram beyond the original minimum and maximum values.

2.1.3. Piecewise Linear Contrast Stretch. When the distribution of an image histogram is a bi- or tri-modal, it is possible to stretch certain values of the histogram to increase contrast enhancement in selected areas. The piecewise linear contrast enhancement involves the identification of a number of linear enhancement steps that can expand the brightness ranges in multiple modes of the histogram. Compared to a normal linear contrast stretch which stretches the minimum and maximum values to the values of lowest and highest gray levels linearly at a constant level of intensity, the piecewise linear contrast stretch defines several breakpoints that increase or decrease the contrast of the image for a given range of values. A low-slop of an image histogram produces a lower contrast for the same range of values. On the other hand, a high-slop of an image histogram produces a higher contrast for the same range of values. So, the higher the slope, the narrower the range of values mapped from the x-axis. This approach creates a wider spread output for the same original values, thus increasing the contrast for that range of values. A piecewise stretch method performs a series of small min-max stretches within a single histogram and is very useful in contrast enhancement. This benefit is traded off for that image analysts must be very familiar with the modes of the histogram and the features they represent in the real world to take advantage of.

2.2. Nonlinear Contrast Enhancement. Nonlinear contrast enhancement often involves histogram equalization, which requires an algorithm to accomplish the task. One major disadvantage resulting from the nonlinear contrast stretch is

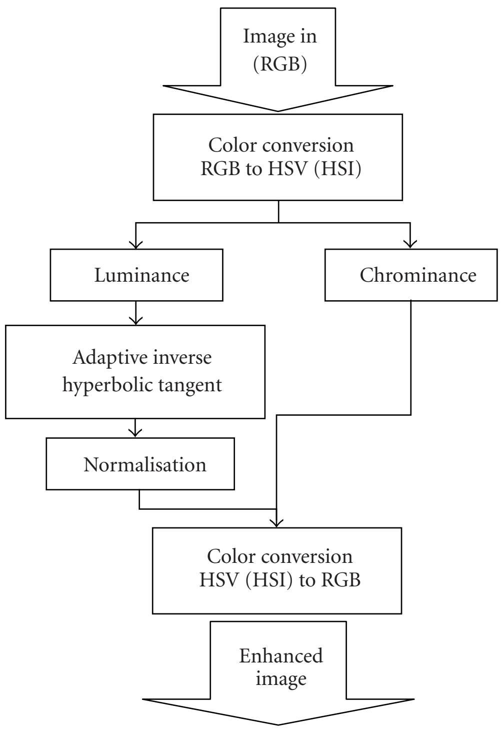


FIGURE 7: A flowchart of the AIHT algorithm.

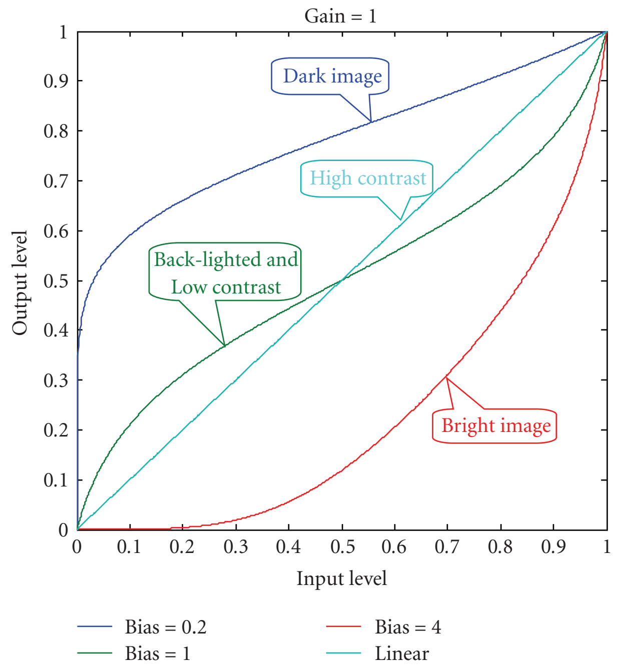


FIGURE 9: AIHT is approximately linear over the middle range values, where the choice of a semisaturation constant determines how input values are mapped to display values.

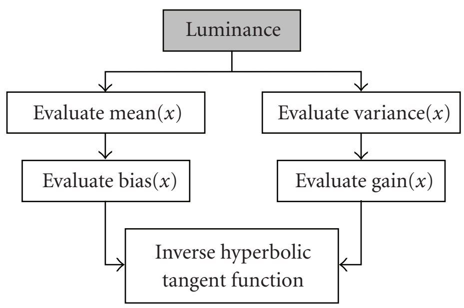


FIGURE 8: A flowchart of AIHT parameters evaluates.

that each value in the input image can have several values in the output image so that objects in the original scene lose their correct relative brightness values. There are two methods of nonlinear contrast enhancement.

2.2.1. Histogram Equalization. Histogram equalization is one of the most useful forms of nonlinear contrast enhancement (Gonzalez and Woods [9]). When an image's histogram is equalized, all pixel values of the image are redistributed. As a result, there are approximately an equal number of pixels for each of the user-specified output gray-scale classes (e.g., 32, 64, and 256). Contrast is increased at the most populated range of brightness values of the histogram (or "peaks"). It automatically reduces the contrast in very light or dark parts of the image, which are associated with the tails of a normally distributed histogram. Histogram equalization can also separate pixels into distinct groups if there are few output values over a wide range [10].

Image analysts should be aware of the fact that while histogram equalization often provides an image with the most contrast of any enhancement technique, it may also hide much needed information. This technique groups pixels that are very dark or very bright into a very few gray scales. If one is trying to bring out information in terrain shadows, or if there are clouds in the image, histogram equalization may not be appropriate.

Duan and Qiu extended this idea to color images, but the equalized images are not visually pleasing for most cases [11]. When the equalization process is applied to gray-scale images or the luminance component of the color images, regions with overstated contrast usually create visually annoying artifacts. In this case, the visually unsatisfactory results caused by equalization are not acceptable because they give the image an unnatural appearance.

2.2.2. Contrast-Limited Adaptive Histogram Equalization. Contrast-Limited Adaptive Histogram Equalization (CLAHE) is an improved version of Adaptive Histogram Equalization (AHE), both of which overcome the limitations of standard histogram equalization. The CLAHE was originally developed for medical images and has improved enhancement of low-contrast images such as portal films [12].

The CLAHE is a local contrast enhancement technique and operates on small regions in an image, called tiles, rather than the entire image. Each tile's contrast is enhanced

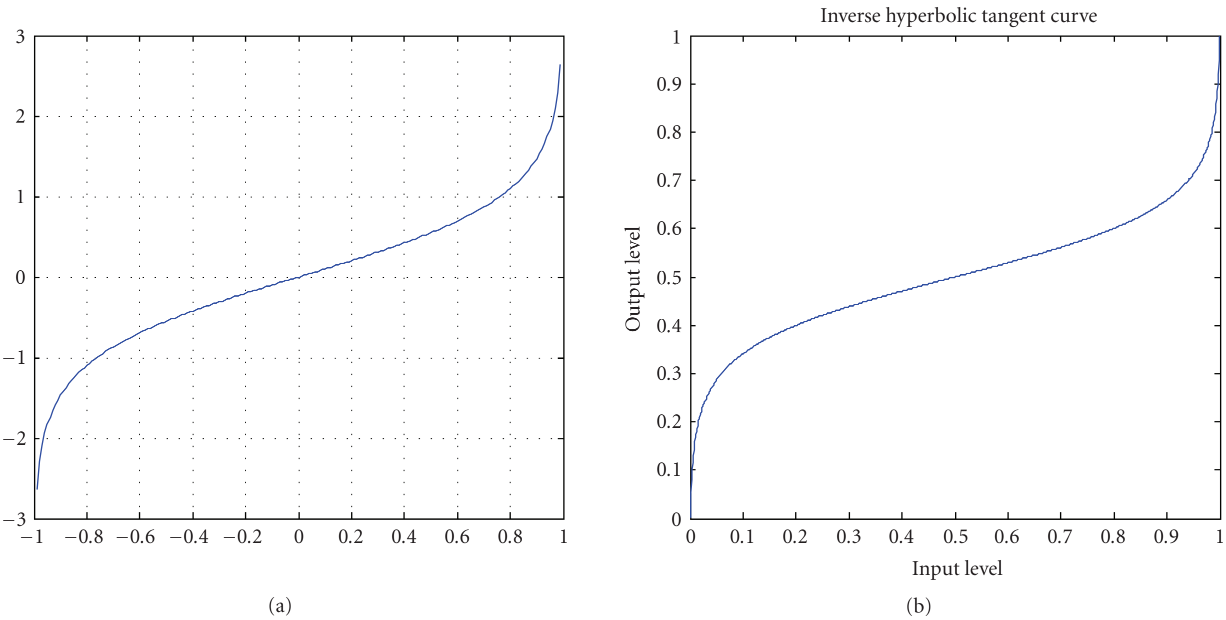


FIGURE 10: Inverse hyperbolic tangent curve: (a) inverse hyperbolic tangent curve, (b) shift to [0, 1].

in such a way that the histogram of the output region approximately matches the histogram specified by the "Distribution" parameter. The neighboring tiles are then combined by bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image. In other words, the CLAHE partitions an image into a set of contextual regions and applies the histogram equalization to each one of them. This evens out the distribution of used grey values and thus makes hidden features of the image more visible. The full gray level spectrum is used to express the image [13].

2.2.3. Logarithm Curve. Using a logarithm curve for contrast enhancement is usually performed for images with low complexity. Stockham was the first to discuss the advantages of this technique [14]. In a later report [15], Drago et al. presented a perception-motivated tone mapping algorithm for interactive display of high contrast scenes. In Drago's algorithm the scene luminance values are compressed using logarithmic functions, which are computed using different bases depending on scene content. The $\log_2$ function is used in the darkest areas to ensure good contrast and visibility, while the $\log_{10}$ function is used for the highest luminance values to reinforce the contrast compression. In-between, luminance is remapped using logarithmic values based on the shape of a chosen bias function. However, this approach has drawbacks: for extreme types of images (such as backlight image, too bright and too dark images), the power function-based image contrast enhancement methods cannot retain the detail brightness distribution of the original image therefore lead to distortion [4].

Bennett and Mcmillan also used a logarithm-like function in his video enhancement algorithm [4, 16]. The difference between a logarithm curve and a gamma curve is that the former obeys the Weber-Fechner law of just noticeable difference (JND) response in human vision but provides a parameter to adapt the logarithmic mapping in a way similar to the log map function. While the high slope of standard gamma correction for low intensities can result in loss of detail in shadow regions.

Contrast masking is one of the most important concepts in human visual systems. In 1987, Whittle presented a concept that complied with this Weber-Fechner law [17] to indicate that larger luminance gradients crossing an image require more stretch than smaller luminance gradients to achieve the same contrast perceived by the human eye. This concept is adopted in our algorithm.

Bennett and Mcmillan [16] and Stockham [14] suggested a simple form of a logarithm curve to enhance the contrast of an image:

$$v(x, y) = \frac{\log(w(x, y) \times (\beta - 1) + 1)}{\log(\beta)}, \qquad (2)$$

where $v(x, y)$ and $w(x, y)$ are the enhanced luminance level and input luminance level, respectively. The parameter β is a control factor that determines the strength of contrast enhancement. Figure 5 shows the relationship between the extent of enhancement and the β value. A larger β value results in more enhancements. This is similar to the gamma function in γ correction (Figure 6). The selection of the β value is crucial. The curve in (2) is designed for global contrast enhancement, in which all pixels share the same β value. The following section describes the method we will use, which is similar to the proposed algorithm.

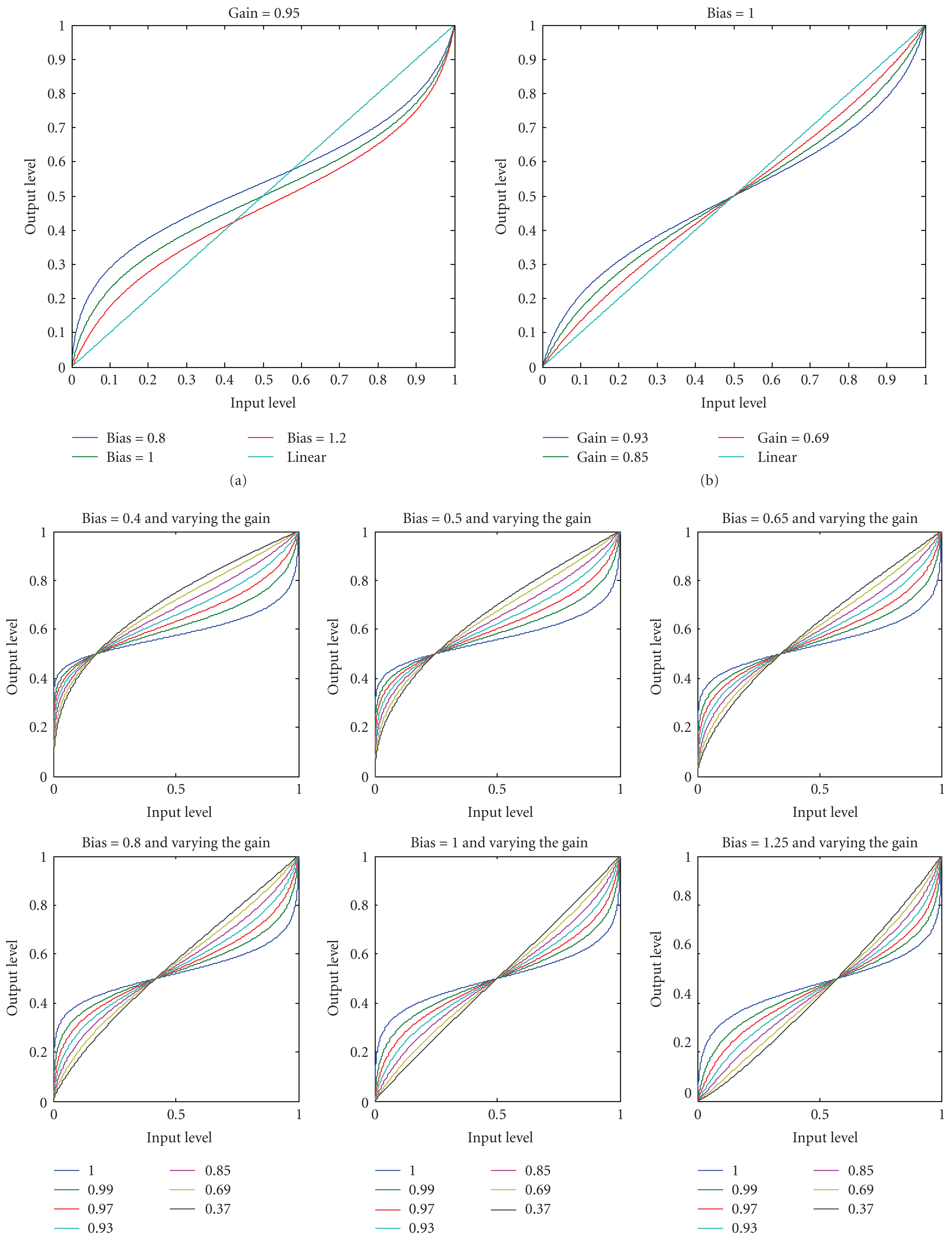
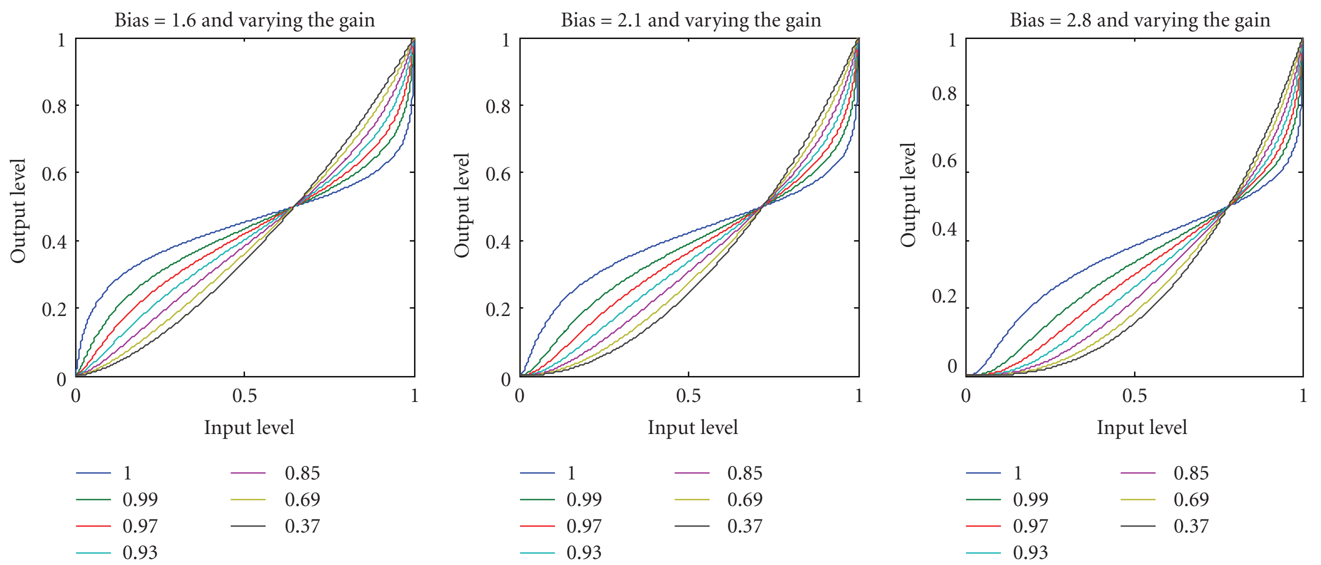


Figure 11: Continued.



(c)

Figure 11: Inverse Hyperbolic Tangent Curve produced by varying the gain and bias values: (a) gain(x) parameter fixed and varying the bias(x) parameter, (b) bias(x) parameter fixed and varying the gain(x) parameter, (c) varying the gain and bias values of mapping curves.

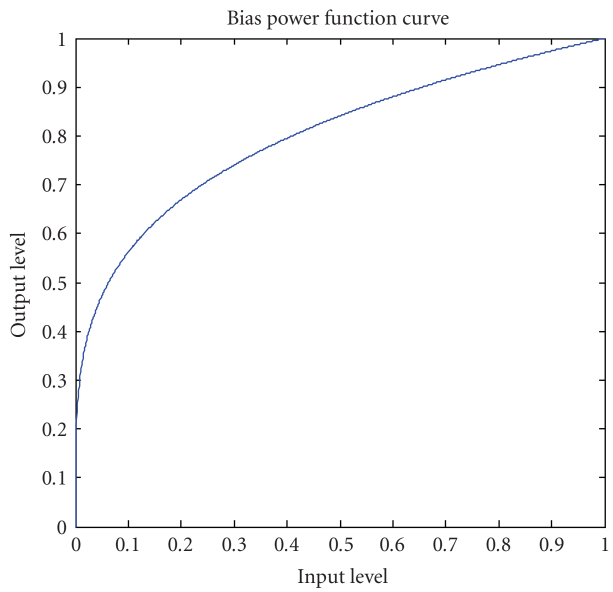


Figure 12: Bias power function curve for different mean's value.

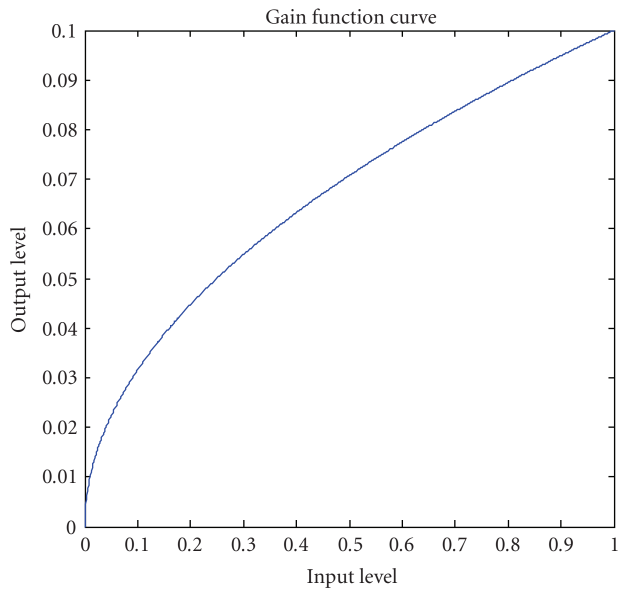


Figure 13: Gain function curve for different variance's value.

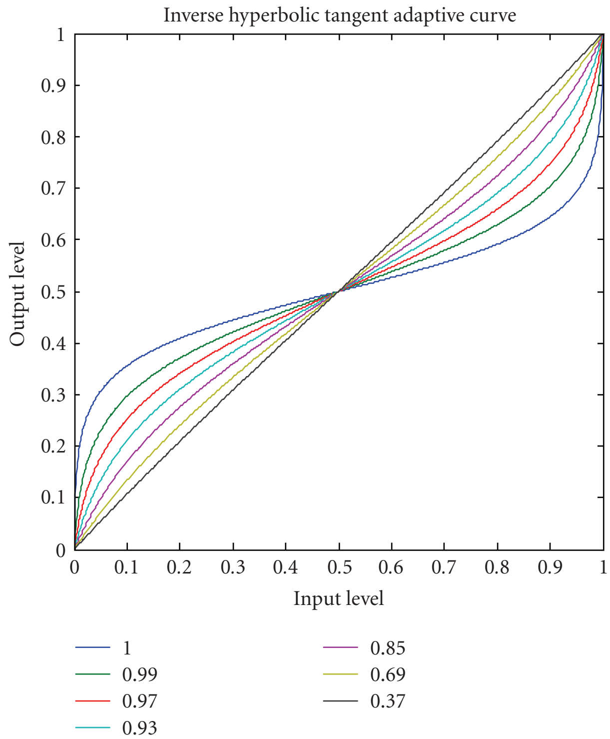
3. Adaptive Inverse Hyperbolic Tangent Algorithm

The proposed Adaptive Inverse Hyperbolic Tangent (AIHT) algorithm automatically converts any color image to a 24-bit pixel format to avoid working with palettes. The HSV (hue, saturation, and value) method is a common approach used for such color-to-gray-scale conversion. In general, a color image can be converted to a gray scale value by computing the luminance value for each color pixel by (3)

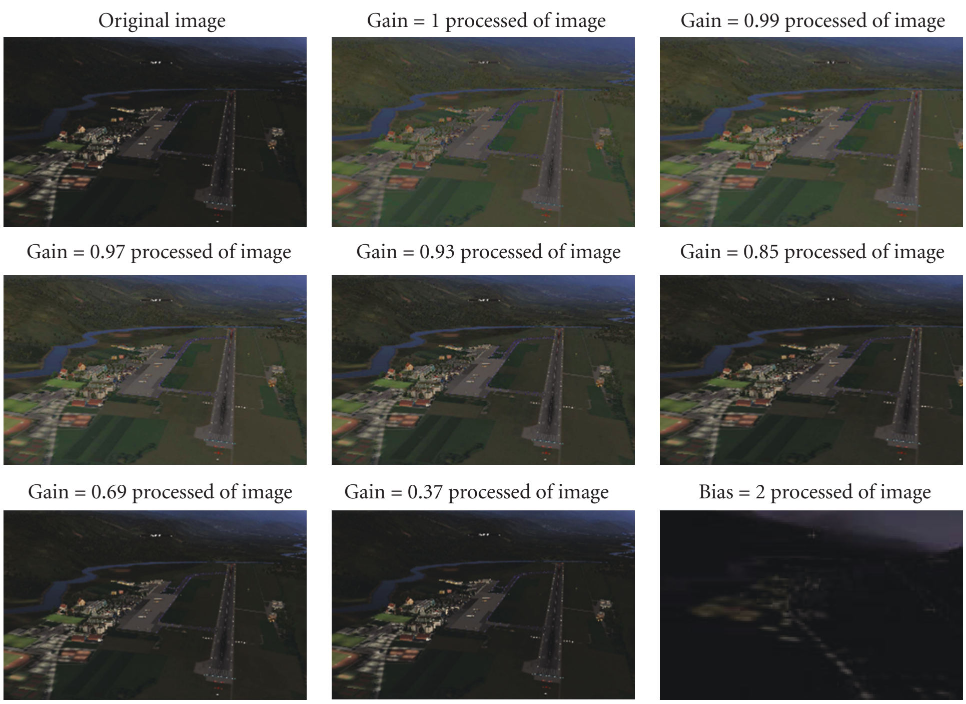
$$\text{Luminance} = \frac{1}{3}(R + G + B). \tag{3}$$

This luminance value is the grayscale component in the HSV color space. The weights reflect the eye's brightness sensitivity to the primary colors.

All the gray levels of the original image must be normalized to the range of $[0, 1]$ before implementing AIHT.

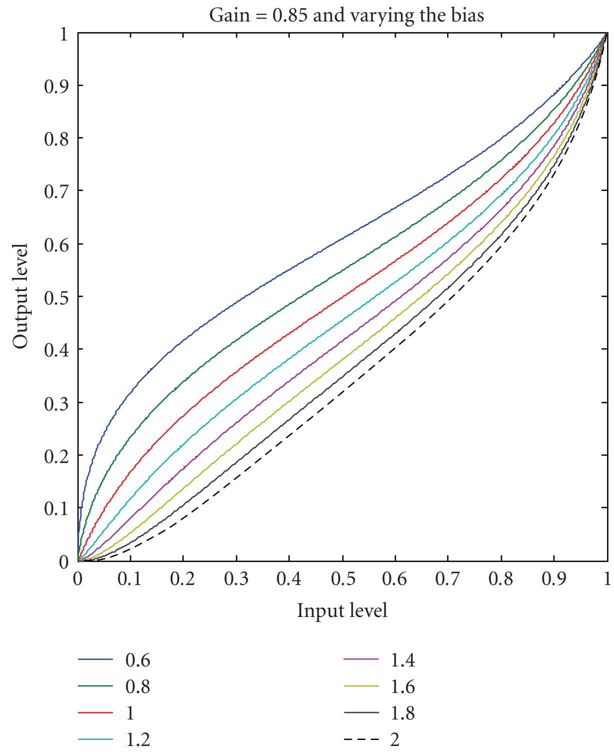


(a)

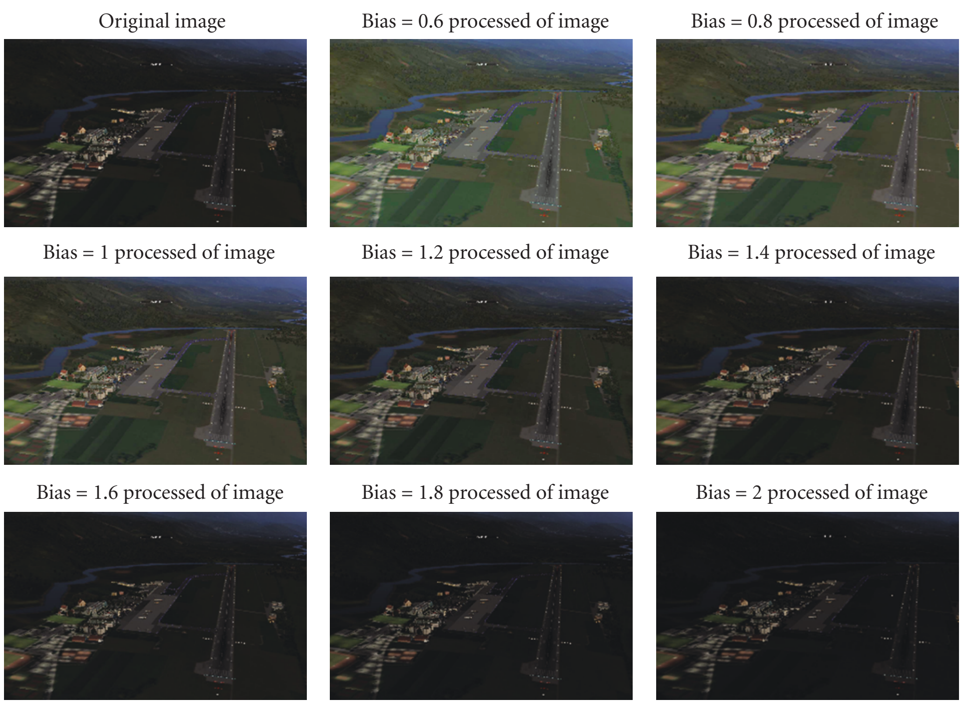


(b)

Figure 14: The gain function determines the steepness of the curve. Steeper slopes map a smaller range of input values to the display range. (a) Bias parameter fixed (bias = 1) and eight different gain values of mapping curves. (b) Fixed bias = 1, processed of images.



(a)



(b)

Figure 15: The value of bias(x) controls the centering of the inverse hyperbolic tangent. (a) Gain parameter fixed (gain = 0.85) and nine different bias values of mapping curves, (b) fixed gain = 0.85, processed of image.

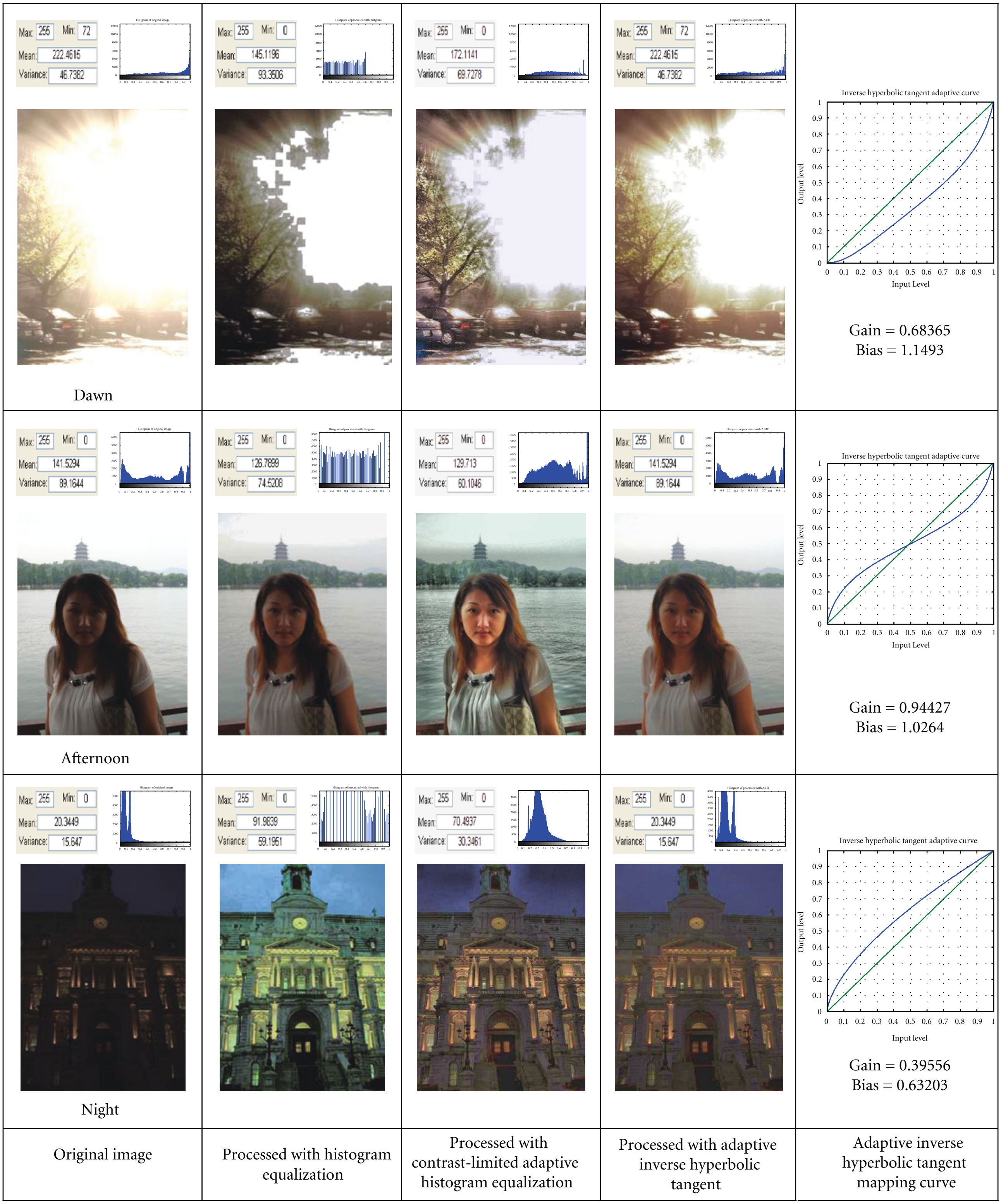


FIGURE 16: Various types of bad contrast images illustrating the difference between contrast enhancement by histogram equalization, contrast limited adaptive histogram equalization, and our method (outdoor images).

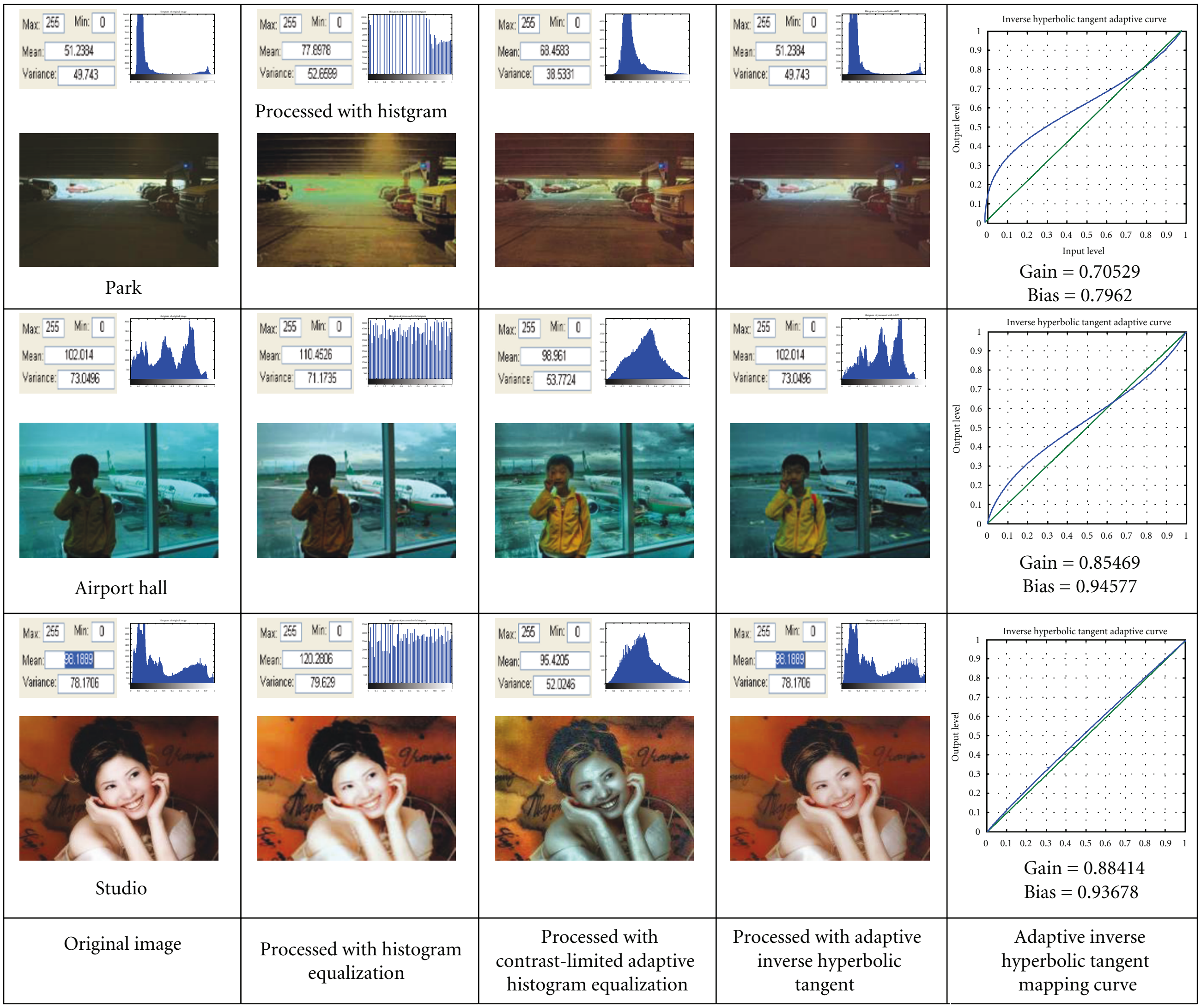


Figure 17: Various types of bad contrast images illustrating the difference between contrast enhancement by histogram equalization, contrast limited adaptive histogram equalization, and our method (indoor images).

Specifically, let x be the gray level of the original image. Then and the normalized gray level g can be obtained by

$$g = \frac{x - \min(x)}{\max(x) - \min(x)}, \tag{4}$$

where $\min(x)$ and $\max(x)$ represent the minimum and maximum gray levels in original image, respectively. Having implemented AIHT, g is mapped to g' using

$$g' = T(a, b, g), \tag{5}$$

where T indicates an AIHT transform, a and b represent parameters to be adjusted. If x' is a gray level of enhanced image, then x' can be expressed as

$$x' = (\max(x) - \min(x))g' + \min(x). \tag{6}$$

Figure 7 shows a block diagram of the AIHT algorithm. The input data is converted from its original format to a floating point representation of RGB values. The principal characteristic of our proposed enhancement function is an adaptive adjustment of the Inverse Hyperbolic Tangent (IHT) Function determined by each pixel's radiance. After reading the image file, the bias(x) and gain(x) are computed. These parameters control the shape of the IHT function. Figure 8 shows a block diagram of AIHT parameters evaluates, including bias(x) and gain(x) parameters.

3.1. AIHT. The Adaptive Inverse Hyperbolic Tangent algorithm has several desirable properties. For very small and very large luminance values, its logarithmic function enhances the contrast in both dark and bright areas of an image. Because this function is an asymptote, the output mapping is always bounded between 0 and 1. Another

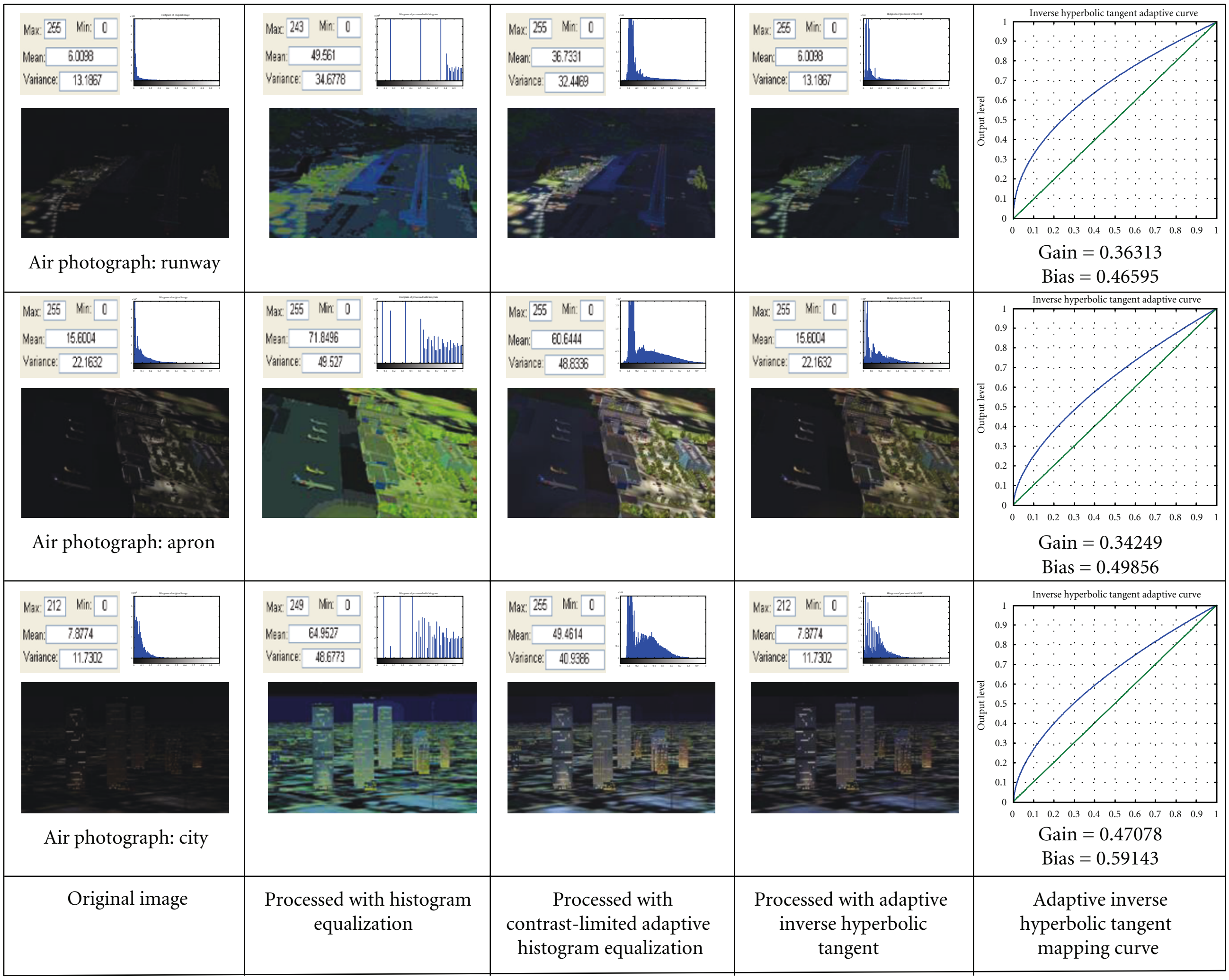


FIGURE 18: Various types of bad contrast images illustrating the difference between contrast enhancement by histogram equalization, contrast limited adaptive histogram equalization, and our method (aerial images).

advantage of this function is that it supports an approximately inverse hyperbolic tangent mapping for intermediate luminance, or luminance distributed between dark and bright values. Figure 9 shows an example where the middle section of the curve is approximately linear.

The form of the AIHT fits data obtained from measuring the electrical response of photo-receptors to flashes of light in various species [18]. It has also provided a good fit to other electro-physiological and psychophysical measurements of human visual function [19–21].

The contrast of an image can be enhanced using inverse hyperbolic function by

$$\tanh^{-1}(x) = \frac{1}{2}\log\left(\frac{1+x}{1-x}\right). \qquad (7)$$

Replace the variable x in (7) with x_{ij}, where x_{ij} is the image gray level of the ith row and jth column. We also put the bias(x) to the power of x_{ij} to speed up the changing. The gain function is a weighting function which is used to determine the steepness of the AIHT curve. A steeper slope narrows a smaller range of input values to the display range. The gain function is used to help shape how fast the mid-range of objects in a soft region goes from 0 to 1. A higher gain value means a higher rate in change. The enhanced pixel x_{ij} is defined as follows:

$$\text{Enhance}\left(x_{ij}\right) = \left(\log\left(\frac{1+x_{ij}^{\text{bias}(x)}}{1-x_{ij}^{\text{bias}(x)}}\right) - 1\right) \times \text{gain}(x). \qquad (8)$$

Therefore the steepness of the inverse hyperbolic tangent curve can be further dynamically adjusted.

Figure 10(a) plots the inverse hyperbolic tangent function over the domain $-1 < x < 1$ with a shift to $0 < x < 1$ domain in Figure 10(b).

3.2. Bias Power Function. Figure 11 shows that the bias(x) value of the inverse hyperbolic tangent function determines the turning points of the curve. If the bias(x) is greater than mean $= 0.5$, then the curve forms a straight line toward the top bending direction. In this case, the pixel

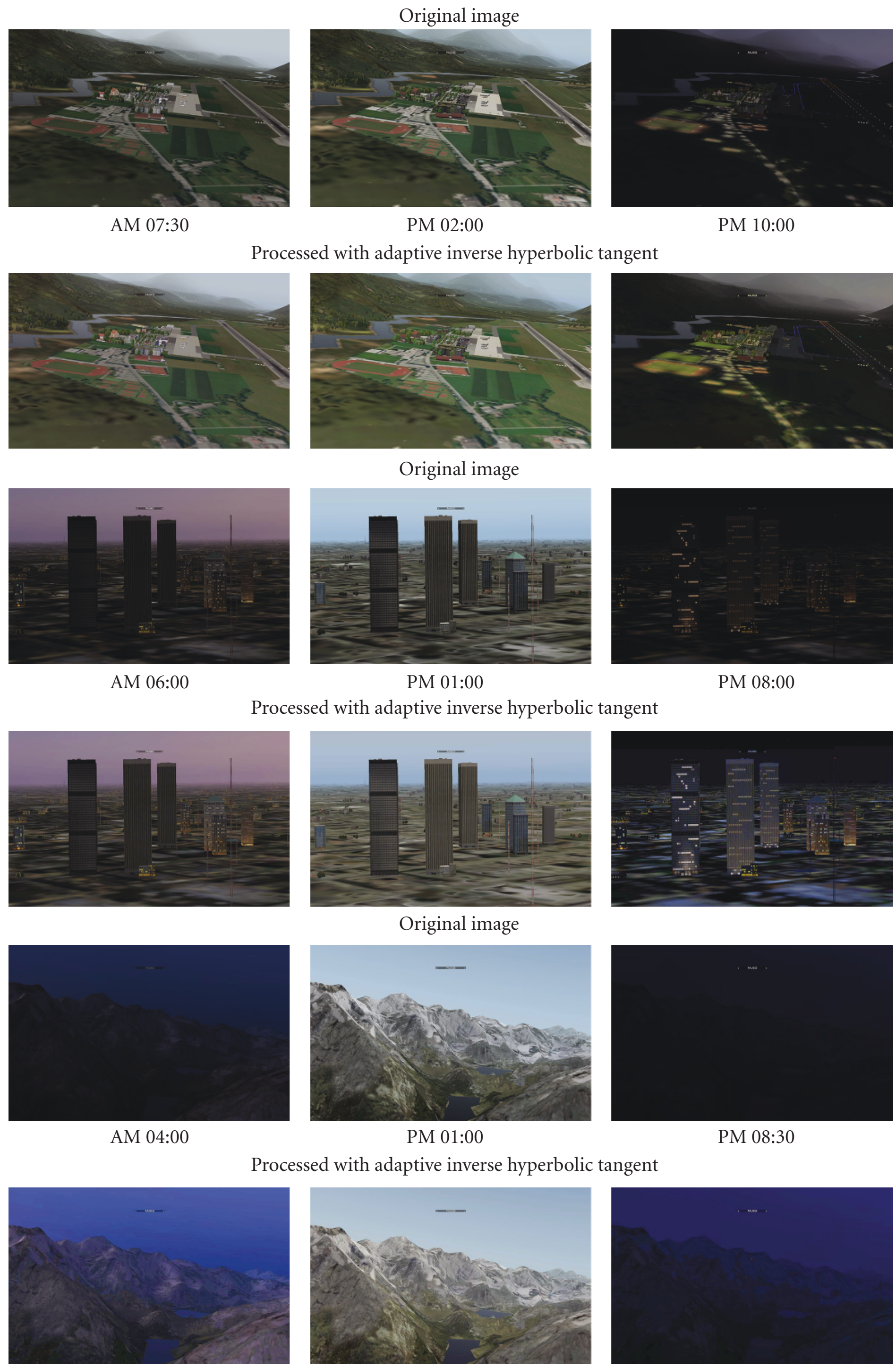


FIGURE 19: Capture images at different times of the contrast enhancement by our method.

value is mapped to a higher value. A bias(x) value less than mean = 0.5 shifts the straight-line portion of the inverse hyperbolic tangent toward lower levels of light. Figure 11(a) illustrates these relationships where gain(x) = 0.5. Similarly, a family of inverse hyperbolic tangent remapping curves can be generated by having the bias(x) parameter fixed such as at mean = 0.5 and varying the gain(x) parameter as shown in Figure 11(b). Decreasing the gain(x) value increases the contrast of the remapped image. Shifting the distribution toward lower levels of light (i.e., decreasing bias(x)) decreases the highlights. By adjusting the bias(x) and gain(x), it is possible to tailor a remapping function with appropriate amounts of image contrast enhancement, highlights, and shadow lightness as shown in Figure 11(c).

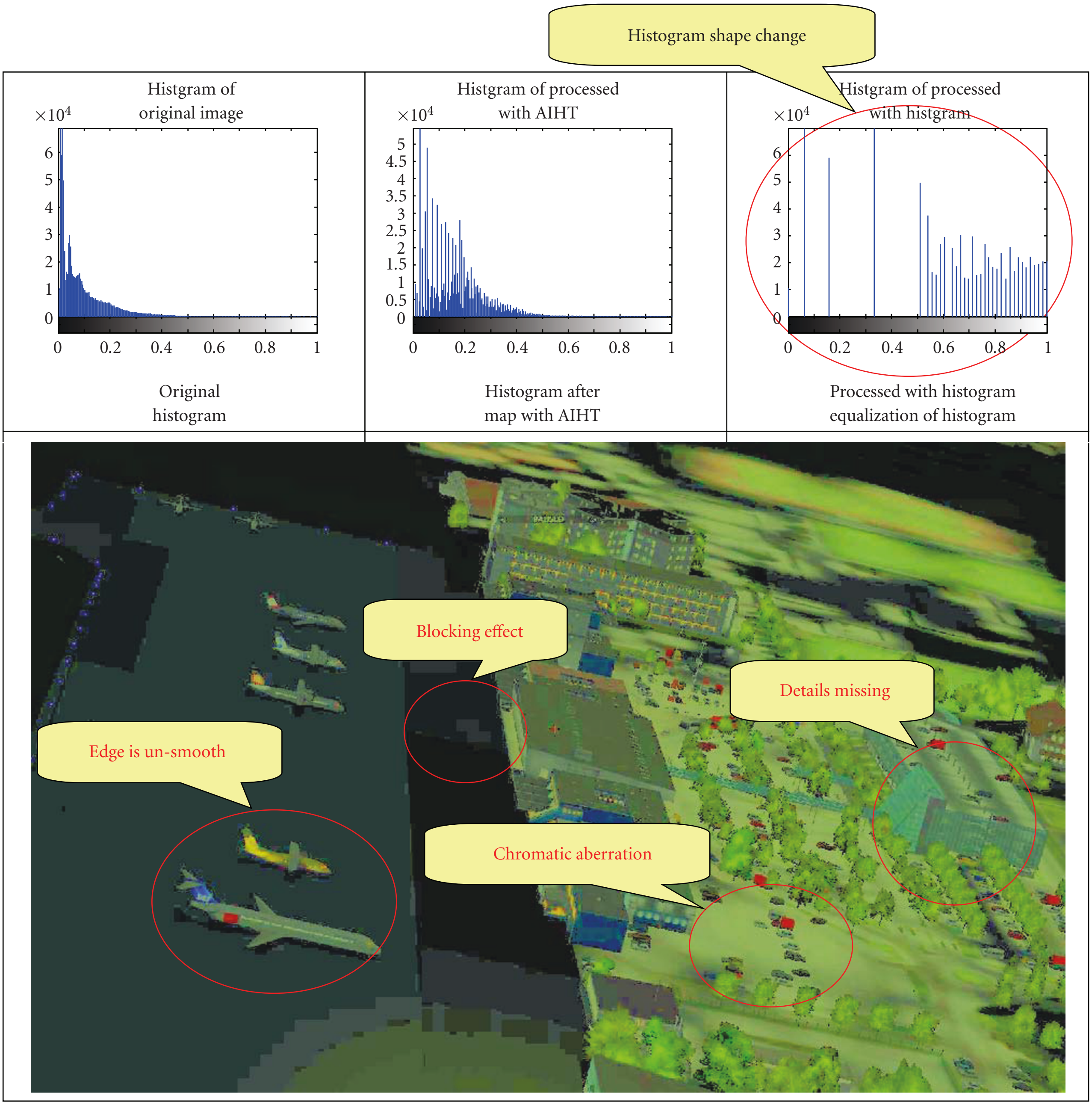


Figure 20: Histogram equalization problems.

To make the inverse hyperbolic tangent curve produce a smooth mapping, we rely on Perlin and Hoffert "bias" function [22]. Bias was first presented as a density modulation function to change the density of the soft boundary between the inside and the outside of a procedural hyper texture. It is a standard tool in texture synthesis and is also used for many different computer graphics tasks. The bias function is a power function defined over the unit interval which remaps x according to the bias transfer function. The bias function is used to bend the density function either upwards or downwards over the $[0, 1]$ interval.

The bias power function is defined by

$$\begin{aligned}\text{bias}(x) &= \left(\frac{\text{mean}(x)}{0.5}\right)^{0.25} \\ &= \left(\frac{(1/(m \times n)) \sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij}}{0.5}\right)^{0.25}.\end{aligned} \tag{9}$$

Figure 12 shows the bias curve for different mean values.

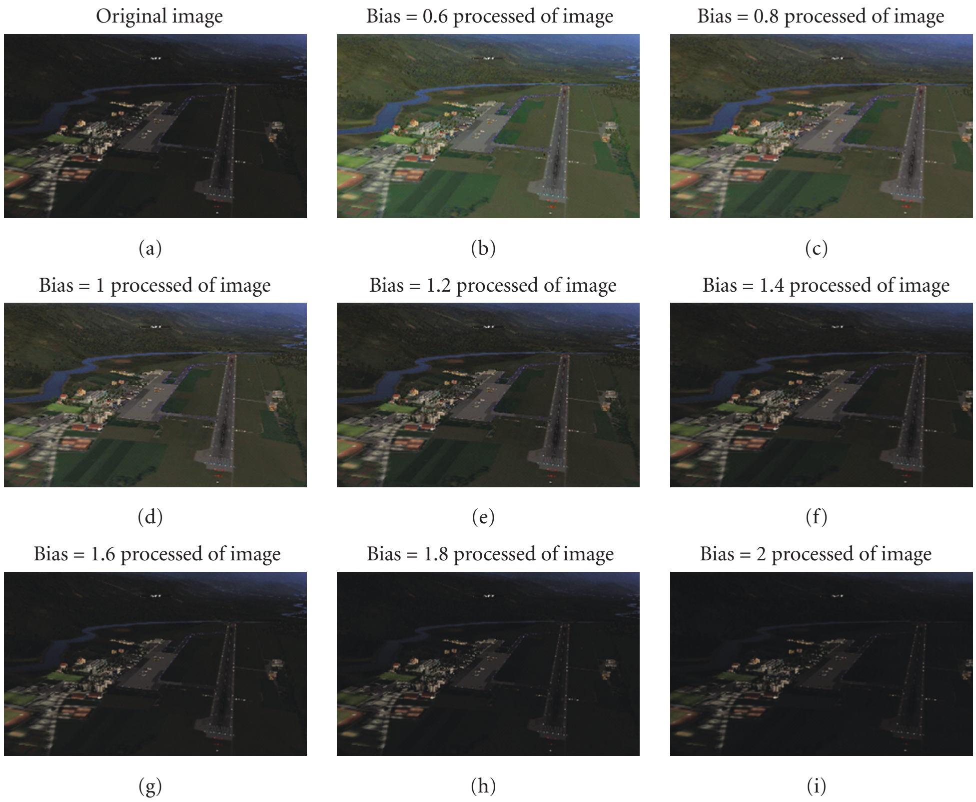


Figure 21: (a) is a bad contrast image, (b)–(i) illustrate results using the proposed method with different factors, yielding different scales of enhanced image details.

3.3. Gain Function. The gain function determines the steepness of the AIHT curve. A steeper slope maps a smaller range of input values to the display range. The gain function is used to help to reshape the object's midrange from 0 to 1 of its soft region.

The gain function is defined by

$$\begin{aligned}\operatorname{gain}(x) &= 0.1 \times (\operatorname{variance}(x))^{0.5} \\ &= 0.1 \times \left(\frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(x_{ij} - \mu \right) \right)^{0.5},\end{aligned} \tag{10}$$

where

$$\mu = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij}. \tag{11}$$

Figure 13 shows the gain curve for different mean values. The gain function determines the steepness of the AIHT curve.

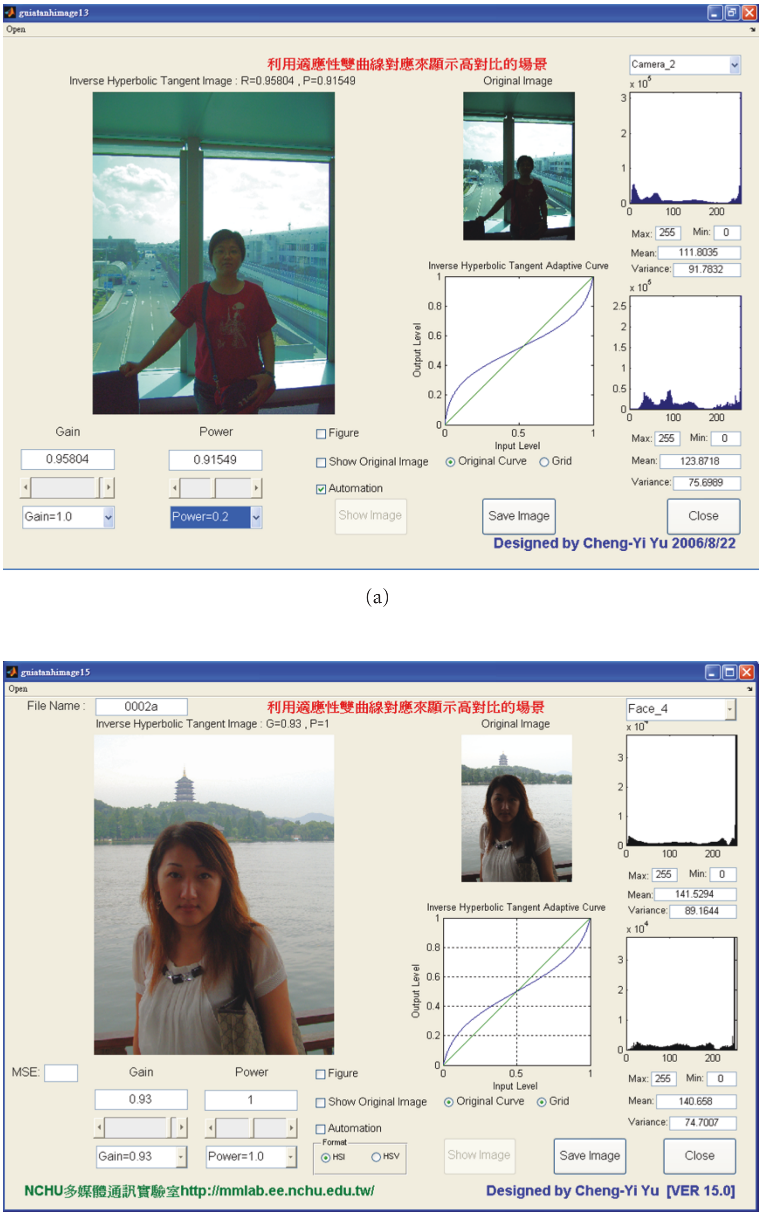
Figure 14 shows the gain curve for different gain values of mapping curves and processed images. There are a total of eight gain values (1, 0.99, 0.97, 0.93, 0.85, 0.69, 0.37), mapping curves as shown in Figure 14(a). The corresponding results are shown in Figure 14(b).

Figure 15 shows processed images and the bias curve for different bias values used by mapping curves. There are a total of nine bias values (0.4, 0.5, 0.65, 0.8, 1.0, 1.25, 1.6, 2.1, 2.8), mapping curves as shown in Figure 15(a). The corresponding results are shown in Figure 15(b).

4. Implementation and Experimental Results

Images with different types of histogram distributions were tested for experiments. These include some daily life images that may arise in contrast to the poor image and demonstrate the enhanced results. The images are categorized into outdoor, indoor, and aerial images. The outdoor images include dawn, afternoon, and night images. The indoor images include park, hall, and studio images. The aerial images include runway, apron, and city images. There are four types of extreme images: dark image, bright image, back-lighted image, and low-contrast image. Figures 16, 17, and 18 show various types of images with bad contrast enhancement. Figures 16, 17, and 18 display the results of the enhanced image processing by histogram equalization, contrast limited adaptive histogram equalization, and the proposed AIHT method. Figures 16–18 show outdoor images, indoor images, and aerial images, respectively. Table 1 lists the values of gain and bias parameters used for the AIHT method. Table 2 compares results by histogram equalization, contrast limited adaptive histogram equalization with that produced by the AIHT method using the measures of MSE, SNR, and PSNR, where the AIHT method was better than histogram equalization and contrast limited adaptive histogram equalization.

The comparative analysis between the proposed methods and currently frequently used methods has showed the effectiveness of these methods. CLAHE improved the local



(b)

Figure 22: The user interface of the AIHT system: (a) automatic mode, (b) manual mode.

Table 1: Gain and bias parameters.

Type	Name	Gain	Bias
Outdoor images	Dawn	0.684	1.149
	Afternoon	0.944	1.026
	Night	0.396	0.632
Indoor images	Park	0.705	0.796
	Hall	0.855	0.946
	Studio	0.884	0.937
Aerial images	Runway	0.363	0.466
	City	0.342	0.499
	Apron	0.470	0.591

contrast of the poor images. The AIHT technique can keep the sharpness of defects' edges well. Therefore, CLAHE and AIHT can greatly enhance poor image and they will be helpful for defect recognition.

Figure 19 shows images captured at different times of the contrast enhancement by the AIHT method. Comparing these ongoing processing results, we can see that histogram equalization and contrast limited adaptive histogram equalization produces grave chromatic aberration, blocking effects, missing details, rough edges. Furthermore, there is also a histogram shape change issue as well (Figure 20). Our approach has no chromatic aberration, blocking effects, missing details, or rough edges and still maintains the original histogram shape.

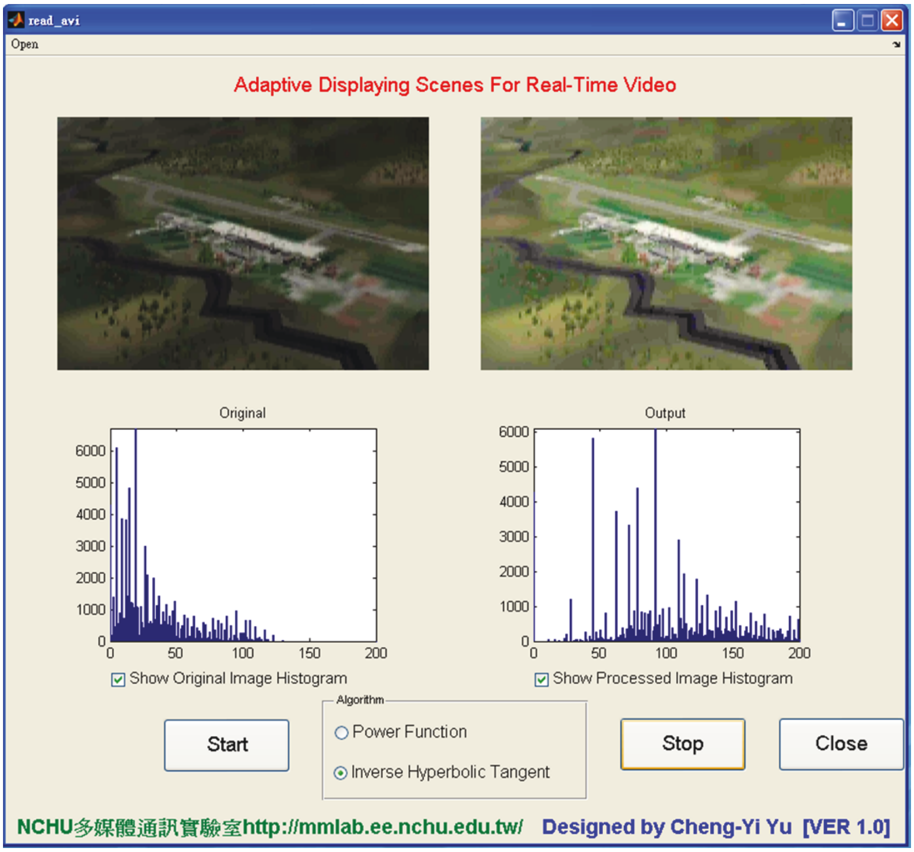


Figure 23: Enhancing the real-time image using the AIHT system.

Table 2: MSE, SNR, and PSNR.

Type	Name	Adaptive inverse hyperbolic tangent			Histogram equalization			Contrast limited adaptive histogram equalization		
		MSE	SNR	PSNR	MSE	SNR	PSNR	MSE	SNR	PSNR
Outdoor images	Dawn	0.0386	22.1137	25.8902	0.16913	5.0272	5.9127	0.0432	10.316	23.143
	Afternoon	0.0099	45.0963	101.170	0.00961	46.391	104.08	0.0432	10.316	23.143
	Night	0.0174	0.85413	57.3469	0.16739	0.0890	5.9741	0.0596	0.2499	16.780
Indoor images	Park	0.0034	28.8848	295.286	0.05862	1.6688	17.060	0.0339	2.8852	29.495
	Hall	0.0163	22.1386	61.4400	0.00206	175.15	486.08	0.0492	7.3229	20.323
	Studio	0.0157	21.0555	63.6445	0.02702	12.245	37.013	0.0561	5.8972	17.825
Aerial images	Runway	0.0125	1.78040	79.7332	0.07680	0.0533	13.021	0.0369	0.1109	27.098
	City	0.0214	0.18545	46.6504	0.11459	0.0347	8.7265	0.0575	0.0691	17.381
	Apron	0.0125	1.07540	80.3171	0.12156	0.1102	8.2265	0.0585	0.2289	17.098

Finally, Figure 21 demonstrates the multiscale property of the AIHT method. The original image (Figure 21(a)) has bad contrast. Figures 21(b)–21(i) presents the results produced by the AIHT method using different factors to yield different scales of enhanced image details. Figure 22 shows the AIHT system interface in manual and automatic mode. The automatic mode adjusts the best parameters (*gain* and *bias*) based on the automatic calculation of characteristics of images (*mean* and *variance*) (Figure 22(a)). In manual mode, users can select their own personal preference to adjust the parameters (Figure 22(b)). The AIHT method can also adjust the contrast of real-time-processed images as shown in Figure 23.

5. Conclusions

This paper presents an effective approach to image contrast enhancement. The proposed algorithm uses an Adaptive Inverse Hyperbolic Tangent algorithm as a contrast function to map from the original image into a transformed image. This algorithm can improve the displayed quality of contrast in the scenes and offers the efficiency of fast computation.

Experimental results show that it is possible to maintain a large portion, if not all, of the perceived contrast of lightness while enhancing the image contrast significantly. The form of these curves used for enhancement was determined based on a simple series of interpolations from a set of optimized reference curves. The proposed algorithm can make the user correctly identify the target as well as dynamically adjust the parameter by using the multiscale method. Experimental results also show that the new algorithm can adaptively enhance image contrast and produce better visual quality than histogram equalization and contrast-limited adaptive histogram equalization. In addition, it can also be implemented in real time in various monitor systems. For overexposed and underexposed images the proposed algorithm also shows great benefit in improving contrast enhancement with no effects resulting from environments. It is our belief that these functions will play a crucial role in developing a more universal approach to color gamut mapping.

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