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Image contrast enhancement based on a three-level adaptive inverse hyperbolic tangent algorithm

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An image contrast enhancement algorithm using a three-scale adaptive inverse hyperbolic tangent (3SAIHT) scheme is proposed. It has long been known that the human vision system heavily depends on details and edges in understanding its perception of scenes. The main goal of this article is to develop a contrast enhancement technique to restore a blurred and dark image so as to improve visual quality. The proposed technique consists of two steps, sub-scaling and contrast enhancement where the sub-scaling is performed by sub-band processing, while the contrast enhancement is accomplished by an AIHT algorithm to bring out hidden details in a processed image. Experimental results show that the proposed method performs better than other techniques.

Keywords: three-scale; sub-band; adaptive inverse hyperbolic tangent; contrast enhancement

1. Introduction

There are many images that are ambiguous and blurred due to acquisition environments such as darkness, shadows, low illumination. Examples of working with these vague aspects include determining the border of a blurred object and determining which gray values of pixels are bright and which are dark (Haubecker and Tizhoosh 2000). Sometimes, an image may be too dark to recognize objects or scenery contained in the image. Thus, image enhancement has been widely used to improve the appearance of an image so that the enhanced image can be easier to analyze and interpret (Jenson 2005). However, the objective of image enhancement is determined by an application context and criteria used for enhancement are often subjective or too complex to be useful for objective measures. While 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.

In this article, a three-scale image enhancement method based on an adaptive inverse hyperbolic tangent (AIHT) algorithm is developed to remedy the above-mentioned shortcomings that generally plague image contrast enhancement methods. The proposed method includes two major processing techniques: (1) a sub-scaling method to achieve sub-band contrast enhancement and (2) a method capable of processing various types (dark image, bright image, back-lighted image, low-contrast image, and high-contrast image (Yu *et al.* 2009, 2010a)) of images so as to enhance and retain the original image details for further image analysis.

This article is organized as follows: Section 2 reviews previous work in the literature. Section 3 develops the three-scale AIHT (3SAIHT) contrast enhancement algorithm. The experiments are conducted in Section 4 by applying our proposed method to real images. Finally, a conclusion is included to provide future directions for further work in contrast enhancement.

2. Contrast enhancement for an image

Contrast enhancement is frequently referred to as one of the most important issues in image processing. Contrast is created by the difference in luminance reflected from two adjacent surfaces. If an image is low contrast and dark, we wish to improve its contrast and brightness. In a digital image, suitable image processing can help to reconcile some of the problems faced in

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the display of digital images. Images often contain large contrast variations and important low-contrast details at the same time. Suitable post-processing can help to meet the conflicting requirements of reproducing the low-contrast details without clipping the general gray-value range. Contrast is an important factor in many subjective evaluations of image quality. Many algorithms for accomplishing contrast enhancement have been developed and applied to problems in various types of imaging. In general, it is possible to discriminate between two classes of contrast corrections: point operations which are global and spatial neighborhood techniques which are local.

Global contrast enhancement algorithms sometimes come with undesired drawbacks, like the loss of tiny details, enhancement of image noise, occasional over enhancement and an unnatural look to the processed images. Using global contrast corrections, it is difficult to accommodate both lowlight and highlight details. On the other hand, local contrast enhancement tries to enhance the visibility of local details in an image. Local contrast enhancement maps one input value to many different output values, depending on the values of the neighboring pixels, and, allowing in this way, for simultaneous shadow and highlight adjustments. Locally enhanced images look more attractive than the originals because of the higher contrast (Smith and Docef 1999).

An advantage of using a global method is its high efficiency and low computational load. On the other hand, a drawback of using a global method is its inability to reveal image details of local luminance variation. On the contrary, an advantage of a local operator is its capability to reveal the details of luminance levels of information in an image at the expense of very high computational cost that may not be suitable for video applications without hardware realization (Haubecker and Tizhoosh 2000, Jenson 2005). Two types of global contrast enhancement techniques, linear, and non-linear are discussed as follows.

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 most suitable for remotely sensed images with Gaussian or near-Gaussian histograms.

Non-linear contrast enhancement often involves histogram equalization (HE), which requires an algorithm to accomplish the task. One of the major disadvantages resulting from the non-linear contrast stretch is 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. Under such a circumstance, the contrast enhancement is generally performed to expand gray level range to mitigate the problem. Recently, several algorithms to address this issue have been developed among which histogram modification techniques are attractive due to their simplicity. HE is a technique that generates a gray map which changes the histogram of an image and redistributes all pixel values to be as close as possible to a user-specified desired histogram (Pizer *et al*. 1987, Korpi-Anttila 2003). A disadvantage of using this method is that it is indiscriminate and produces unrealistic effects. It may also increase the contrast of background noise, while decreasing the usable signals. In scientific imaging where spatial correlation is more important than intensities of signals, a small signal to noise ratio usually hinders visual detection.

3. Three-scale parameter adjustment of AIHT algorithm

3.1. *AIHT algorithm*

The AIHT enhancement algorithm is an adaptive adjustment of the 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 (Haubecker and Tizhoosh 2000, Jenson 2005). The AIHT algorithm uses the $bias(x)$ to the power of x to speed up changing. The $gain(x)$ function is a weighting function which is used to determine the steepness of the AIHT curve. It 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 outputs are always bounded between 0 and 1. Another advantage of using this function is that it supports an approximately IHT mapping for intermediate luminance, or luminance distributed between dark and bright values.

The form of the AIHT algorithm fits data obtained from measuring the electrical response of photoreceptors to flashes of light in various species (Naka and Rushton 1966). It has also provided a good fit to other electro-physiological and psychophysical measurements of human visual function (Kleinschmidt and Dowling 1975, Hood and Finkelstein 1979, Hood *et al*. 1979).

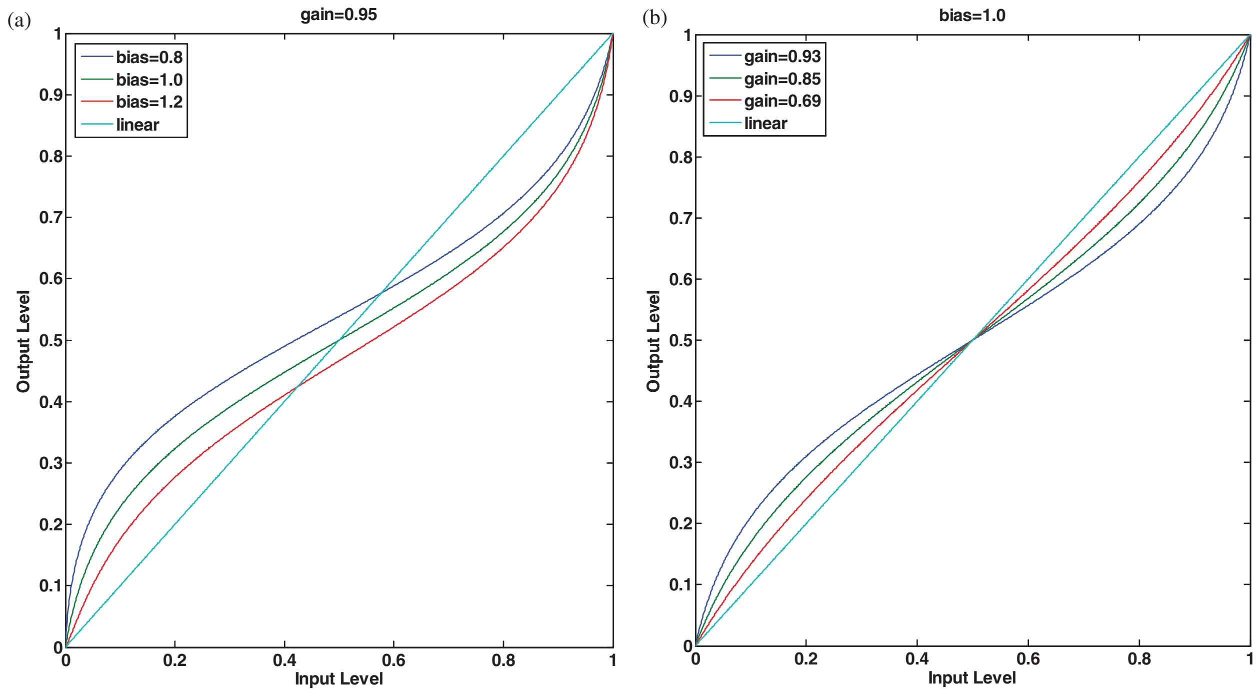

Figure 1. IHT curve produced by varying the *gain* and *bias* values: (a) *gain* parameter = 0.95 and different *bias*(x) parameters; (b) *bias* parameter = 1.0 and different *gain*(x) parameters; and (c) mapping curves for different *gain* and *bias* values.

The contrast of an image can be enhanced using adaptive inverse hyperbolic function via the following function:

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

where x_{ij} is the image gray level of the ith row and jth column.

The *bias* function is a power function defined over the unit interval which remaps x according to a *bias* transfer function which is used to bend the density function either upwards or downwards over the [0,1] interval. It is defined by

$$bias(x) = \left(\frac{mean(x)}{0.5}\right)^{0.25} = \left(\frac{\frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n}x_{ij}}{0.5}\right)^{0.25} \quad (2)$$

The *gain* function determines the steepness of the AIHT curve. It is used to help to reshape the object's mid-range from 0 to 1 of its soft region for the purpose of nominalization. A steeper slope maps a smaller range of input values to a wider range and a gentle slope maps a wider range of input values to a smaller range. A *gain* function is defined by

$$\begin{aligned} gain(x) &= 0.1\times(\text{variance}(x))^{0.5} \\ &= 0.1\times\left(\frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n}(x_{ij}-\mu)\right)^{0.5} \end{aligned} \quad (3)$$

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

Figure 1(a) shows different *bias*(x) values while *gain*(x) value is fixed. If the *bias*(x) is larger than the mean = 0.5, then the curve forms a straight-line bending toward the top. In this case, the pixel value is mapped to a higher value. If a *bias*(x) value is less than the mean = 0.5, the straight-line portion of the IHT shifts toward lower levels of light. Figure 1(a) illustrates these relationships with *gain*(x) = 0.95. Similarly, a family of IHT re-mapping 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 1(b). Decreasing the *gain*(x) value increases the contrast of the re-mapped 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 re-mapping function by appropriate amounts of image contrast enhancement, highlights, and shadow lightness, as shown in Figure 1(c).

The *gain* function determines the steepness of the curve. Steeper slopes map a smaller range of input values to the display range. The value of *bias* controls the centering of the IHT and its scale seamlessly. Figure 2 shows a different set of *gain* and *bias* values for the processed images. There are a total of seven *gain* values (1, 0.99, 0.97, 0.93, 0.85, 0.69, and 0.37) with *bias* parameter fixed (*bias* = 1), the corresponding results are shown in Figure 2(a). A total of eight *bias*

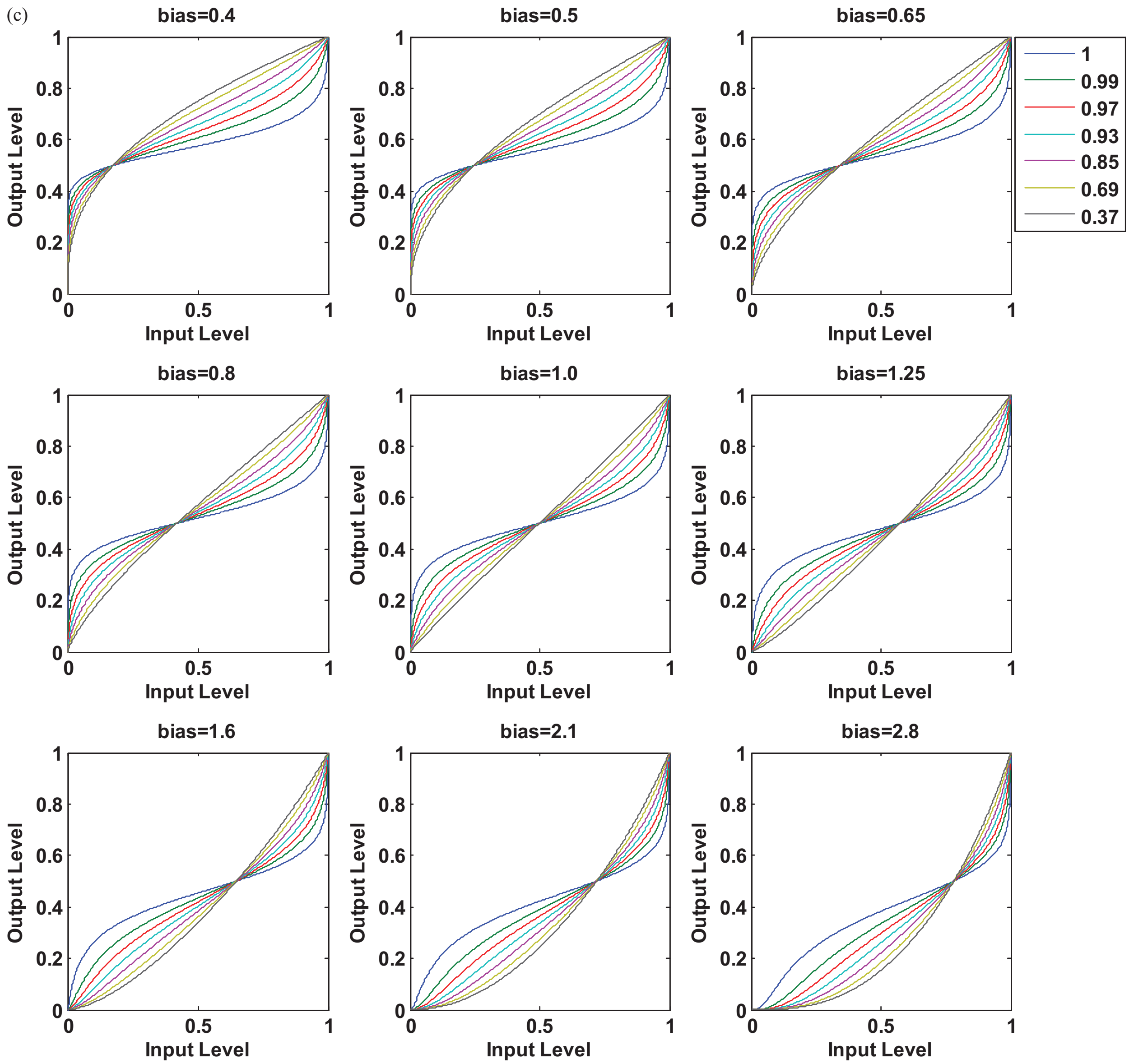

Figure 1. Continued.

values (0.6, 0.8, 1.0, 1.2, 1.4, 1.6, 1.8, and 2.0) with *gain* parameter fixed ($gain = 0.85$) are shown in Figure 2(b).

The AIHT-based image contrast enhancement method has two drawbacks. One is that it lacks a mechanism to adjust the degree of enhancement. The use of the AIHT-based image contrast enhancement methods cannot retain the subtle brightness distribution of the original image; therefore, it may lead to a distortion. Another is that using the AIHT-based algorithm can only be used for global contrast enhancement and cannot enhance local contrast. Therefore, it is unable to meet the human visual system mapping curve and to produce a non-smooth or distorted image phenomenon.

3.2. *Two-scale parameter adjustment of AIHT algorithm*

Figure 3 shows a block diagram of the 2SAIHT algorithm. The input data are converted from its original format to a floating point representation by RGB values. The principal feature of the 2SAIHT function is according to the average of each pixel's radiance and is non-equally divided into low and high bands. The low band is when the pixel's radiance smaller than the average value, other pixels' radiance, larger than average value, are classified in the high band. The *bias*(x) and *gain*(x) are generated from the mean and variance of each sub-band and can

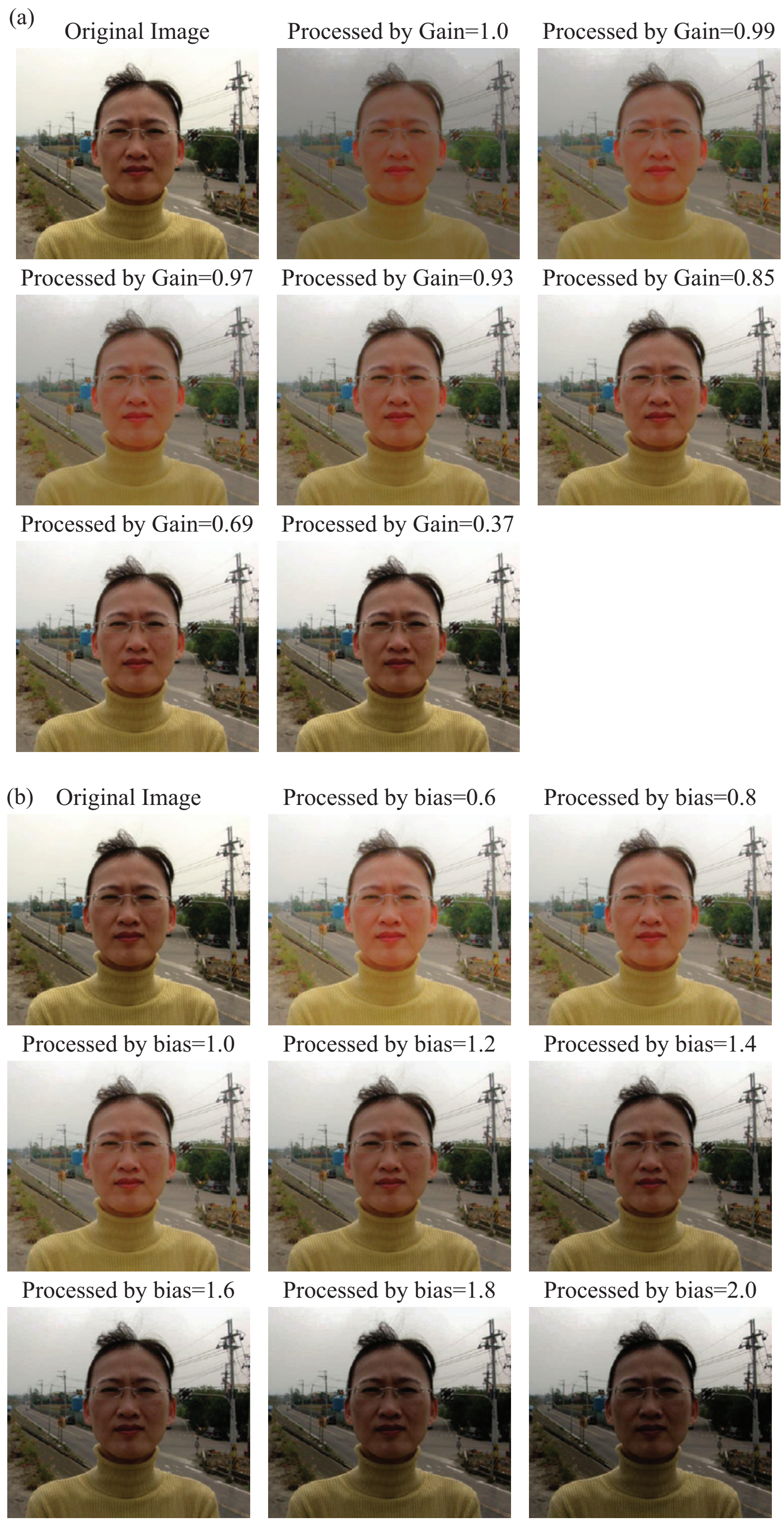

Figure 2. (a) The *bias* parameter is fixed ($bias = 1$) and seven different *gain* values of images and (b) *gain* parameter is fixed ($gain = 0.85$) and eight different *bias* values of mapping curves.

determine the shape of each sub-band using the AIHT function (Yu *et al.* 2010b).

The pixel values through the 2SAIHT process can range from high band to low band. Multi parameters (include $bias_H(x)$, $gain_H(x)$, $bias_L(x)$, and $gain_L(x)$ parameters) are generated through the 2SAIHT process. These parameters have strong impact on the shapes of images for different sub-bands. Figure 4 shows a block diagram of using 2SAIHT to generate two-scale parameters, $bias(x)$ and $gain(x)$. The new output image is enhanced. The two-scale approach is described by

$$\begin{aligned} Enhance\_2SAIHT(x) &= \sum_{k=1}^{2} AIHT_{bias(k),gain(k)}(x_k) \\ &= \sum_{k=1}^{2} \left(\log\left(\frac{1 + x_k^{bias_k(x_k)}}{1 - x_k^{bias_k(x_k)}} \right) - 1 \right) \\ &\quad \times gain_k(x_k) \end{aligned} \tag{4}$$

where k is the number of sub-band used and x_k is the sub-band image of input image.

The two-scale method is used to enlarge the lower and higher luminance levels. It can be used to automatically adjust the local gain in the low- and high-luminance images and make the local details become visible. However, the two-scale method ignores

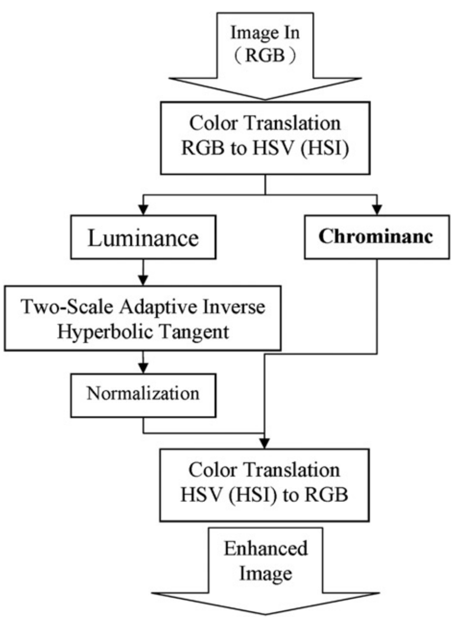

Figure 3. A flowchart of 2SAIHT algorithm.

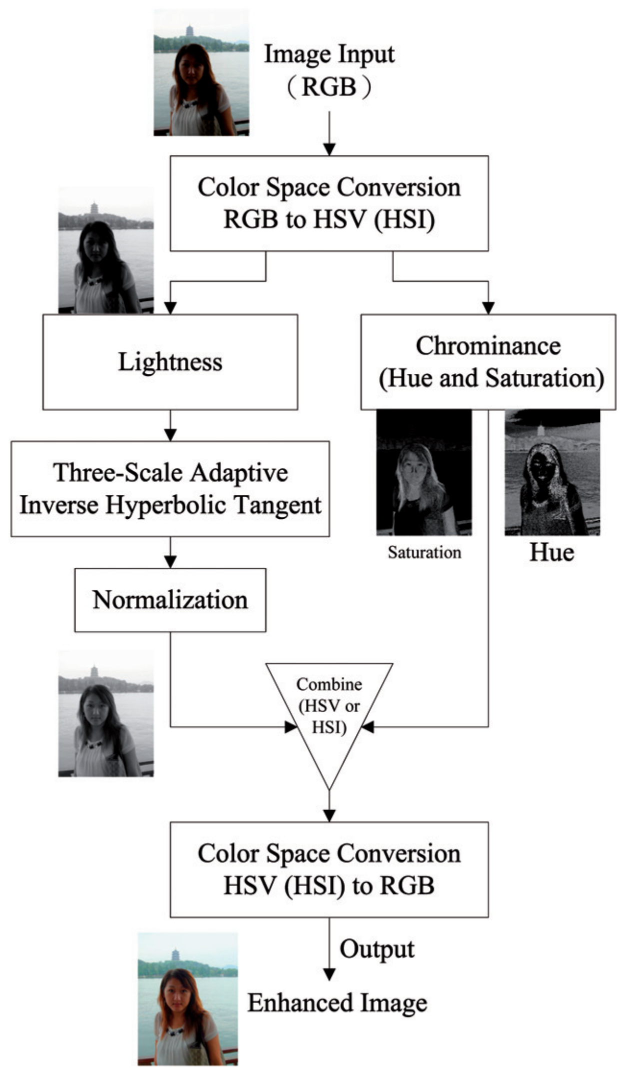

Figure 5. A flowchart of 3SAIHT algorithm.

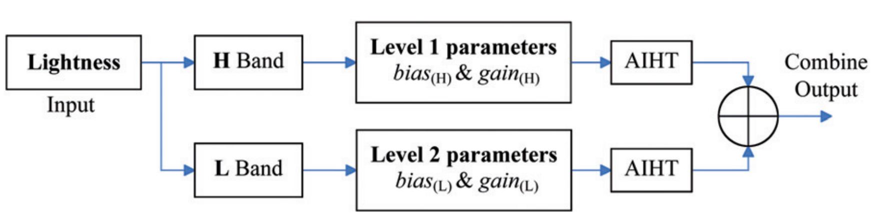

Figure 4. A flowchart of 2SAIHT parameter evaluations.

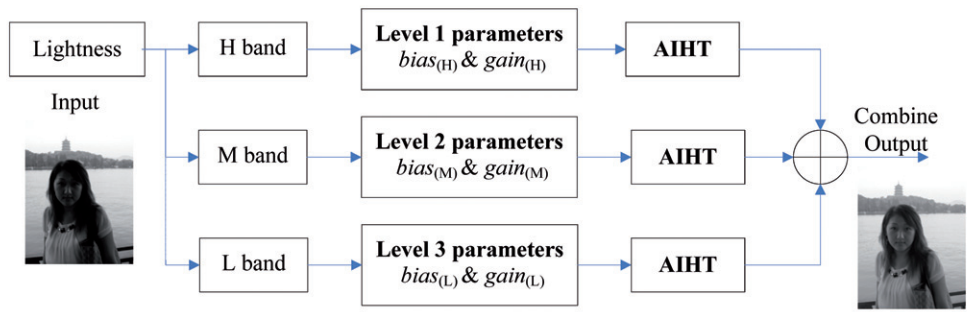

Figure 6. A flowchart of 3SAIHT parameter evaluates.

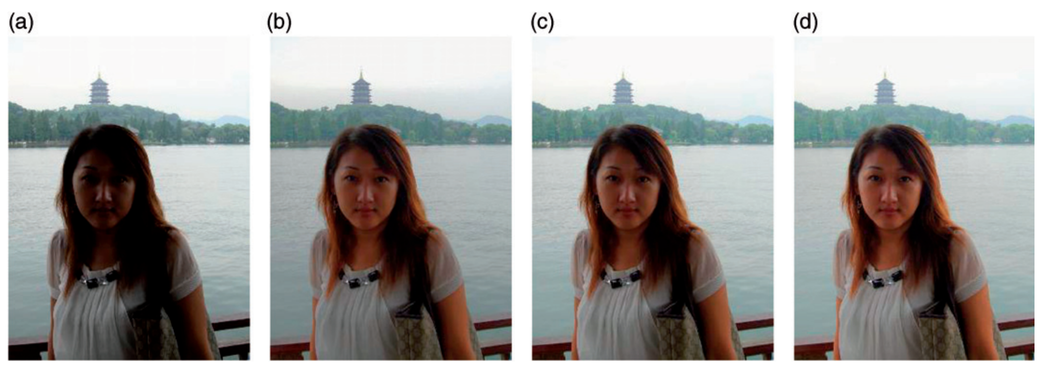

Figure 7. Comparison of AIHT, 2SAIHT, and 3SAIHT algorithm results: (a) original image; (b) processed by AIHT; (c) processed by 2SAIHT; and (d) processed by 3SAIHT.

the medium part of the luminance, hence a potential problem is raised. To solve this problem, we have to provide a transformation function that can also retain linear characteristics for the medium part of the luminance.

3.3. *Three-scale parameter adjustment of adaptive inverse hyperbolic tangent algorithm*

Figure 5 shows a block diagram of the 3SAIHT algorithm. The input data are converted from its original format to a floating point representation of RGB values. Our proposed 3SAIHT algorithm, a further extension from the 2SAIHT algorithm, is different in that pixels can be ranged from high band to medium band and to low band and it can process its own parameters, respectively. The 3SAIHT function is according to the average of all pixels' radiance and is non-equally divided into low and high band. For sub-band (low and high bands) average pixels' radiance and obtain low and high band average. Moreover, it is based on low and high band averages to benchmark and is non-equally divided into high, medium, and low bands of input image. The low band is where pixels' radiance is less than the average value of low band and high band is where pixels' radiance is greater than the average value of high band, other pixels' radiance, between the average value of low and high band, is medium band. The input data are read and different band parameters are also generated (include $bias_H(x)$, $gain_H(x)$, $bias_M(x)$, $gain_M(x)$, $bias_L(x)$, and $gain_L(x)$ parameters). Different sub-band parameters can affect the newly generated image shape. Figure 6 shows a block diagram of using 3SAIHT algorithm to generate three-scale $bias(x)$ and $gain(x)$ parameters.

There are two important goals for our proposed three-scale band design scheme. One is to avoid noise visibility, especially in smooth regions, and the other is to prevent intensity saturation for possible minimum and maximum intensity values (e.g., 0 and 255 for 1 byte per channel source format). This three-scale algorithm for processing input image x is described by

$$\begin{aligned} Enhance\_3SAIHT(x) &= \sum_{k=1}^{3} AIHT_{bias(k),gain(k)}(x_k) \\ &= \sum_{k=1}^{3} \left(\log\left(\frac{1 + x_k^{bias_k(x_k)}}{1 - x_k^{bias_k(x_k)}} \right) - 1 \right) \\ &\quad \times gain_k(x_k) \end{aligned} \tag{5}$$

Figure 8. Various types of bad contrast images illustrating the difference between contrast enhancement by HE, CLAHE, AIHT, 2SAIHT, and our method of 3SAIHT.

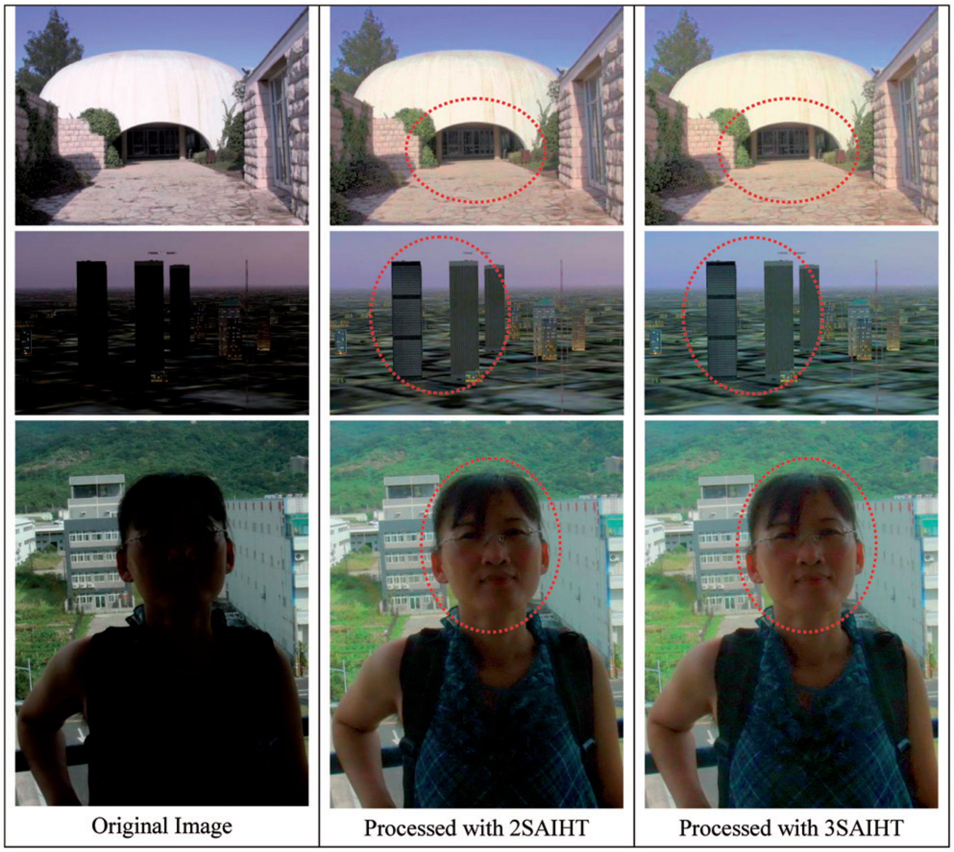

Figure 9. Comparison of 2SAIHT and 3SAIHT.

Table 1. Results compared by various scales of AIHT and run times.

Image resolution	AIHT	2SAIHT	3SAIHT
355 × 505	0.056927	0.095766	0.134760
376 × 565	0.061338	0.104742	0.145727
480 × 640	0.079687	0.139500	0.196609
1280 × 800	0.207015	0.373940	0.580643
2048 × 1536	0.579902	1.130608	1.649544

where k is the number of sub-band used and x_k is the sub-band image of input image.

The above three-scale approach is used to augment the lower, medium, and higher luminance levels. Using the 3SAIHT algorithm can automatically adjust the local gain; therefore the local details (high, medium, and low) can be made visible. An additional benefit of this approach is that it potentially solves the problem caused by compression resulting from the display (the so-called gamma curve). This transformation function has an adaptive enhance rate for any part of the luminance range and hence there are additional details in the low-, medium-, and high-luminance regions. Figure 7 displays the different results of the enhanced image processing by AIHT, 2SAIHT, and 3SAIHT methods.

4. Implementation and experimental results

In this section, we will briefly explain implementation and experimental results. We implement and compare several published algorithms. By combining the advantages of these algorithms and determining the parameters by testing them on known images, we implement an automatic system successfully. All methods mentioned above are used for performance evaluation. There are four extreme types of images: dark image, bright image, back-lighted image, and low-contrast image to be used for experiments. Images with different types of histogram distributions were also tested for experiments. These include some daily-life images that may arise and demonstrate the enhanced results. Figure 8 shows various types of images with bad contrast enhancement and displays the results of the enhanced image processing by HE, contrast-limited adaptive histogram equalization (CLAHE), AIHT, 2SAIHT, and the proposed 3SAIHT method. Figure 9 shows 2SAIHT and 3SAIHT comparison on local detail. For local detail enhancement, using the 3SAIHT method is better than using the 2SAIHT method.

The comparative analysis between the proposed methods and currently frequently used methods has shown the effectiveness of these methods. The 3SAIHT technique can keep the sharpness, detect edges, and local detail as well. Therefore, AIHT, 2SAIHT, and 3SAIHT can greatly enhance those extreme poor images be comprehensible to human eyes and help in defect recognition.

Table 1 presents comparison results achieved by various scales and the needed run times. Increasing the sub-band number will increase the run time. Table 2 presents the result of different mean, variance, gain, and bias parameter values of various scale methods (include AIHT, 2SAIHT, and 3SAIHT). Table 3 presents the comparison results of MSE, SNR, and PSNR by using HE, CLAHE, AIHT, 2SAIHT, and 3SAIHT. The result of image enhancement in general cannot be illustrated by quantification results, but the quantification results of Table 3 could provide some idea about how 3SAIHT transforms outperform than other methods.

Table 2. Parameters value of various scales of AIHT (include AIHT, 2SAIHT, and 3SAIHT).

		3SAIHT		
		2SAIHT		
		AIHT		
		Low band	High band	Medium band
Mean	AIHT	0.5582		
	2SAIHT	0.4786	0.5767	
	3SAIHT	0.2950	0.5767	0.5694
Variance	AIHT	0.3483		
	2SAIHT	0.1715	0.1332	
	3SAIHT	0.0593	0.0451	0.1867
Bias	AIHT	1.0264		
	2SAIHT	0.6212	0.5474	
	3SAIHT	0.3653	0.3185	0.6481
Gain	AIHT	0.9443		
	2SAIHT	0.8318	0.8715	
	3SAIHT	0.7369	0.8714	0.8687

5. Conclusions

A new 3SAIHT method has been presented and promising results have been shown for image contrast interpretation. The adaptive local image enhancement method is based on a simple pixel-wise 'AIHT' correction of the input data by introducing sub-scaling processing for contrast enhancement. The selectivity of non-equally divided benchmark from image features joins with the enhancement ability of AIHT to make this 3SAIHT method significant. Each sub-band parameter, *bias* and *gain*, can dynamically adjust and perform image contrast strength correction, therefore can avoid contrast and color saturation losses which are common drawbacks of contrast enhancement methods. This method has two major features: (1) a sub-band processing method to achieve local contrast enhancement and (2) an extreme case images processing method that is capable of enhancing and retaining the details of an original image. An enhanced image could provide great detail for further image analysis.

Table 3. MSE, SNR, and PSNR evaluate values.

	HE			CLAHE			AIHT			2SAIHT			3SAIHT		
Image type	MSE	SNR	PSNR	MSE	SNR	PSNR	MSE	SNR	PSNR	MSE	SNR	PSNR	MSE	SNR	PSNR
Dawn	0.169	5.027	5.913	0.043	10.32	23.14	0.039	22.11	25.89	0.029	29.48	34.67	0.006	141.5	166.5
Morning	0.078	1.233	12.82	0.039	2.475	25.73	0.008	12.45	129.4	0.023	4.181	43.47	0.036	2.653	27.58
Afternoon	0.010	46.39	104.1	0.043	10.32	23.14	0.010	45.10	101.2	0.007	61.66	138.3	0.011	41.36	92.78
Night	0.122	0.110	8.227	0.058	0.229	17.10	0.012	1.075	80.32	0.032	0.418	31.21	0.043	0.314	23.44

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 proposed algorithm can allow the user to correctly identify the target as well as dynamically adjust parameters by using the three-scale method. In particular, for overexposed and underexposed images, the proposed algorithm also shows a great benefit in improving contrast enhancement. The overall diagnostic sensitivity compares favorably with state-of-the-art enhancement and our previous study of AIHT and 2SAIHT methods, and also circumvents and reduces some of the artifacts associated with existing methods.

Nomenclature

bias	symmetrical function
gain	enhancement function
H	high band
i	ith row
j	jth column
k	number of sub-band
L	low band
m	number of rows in the image
M	medium band
n	number of columns in the image
μ	mean of the intensities in image
x	image intensity
x_k	sub-band image
x_{ij}	image gray level of the ith row and jth column

References

Haubecker, H. and Tizhoosh, H., 2000. *Computer vision and application*. Orlando, FL: Academic Press.

Hood, D.C. and Finkelstein, M.A., 1979. A comparison of changes in sensitivity and sensation: implications for the response intensity function of the human photopic system. *Journal of experimental psychology: human perception and performance*, 5 (3), 391–405.

Hood, D.C., Finkelstein, M.A., and Buckingham, E., 1979. Psychophysical tests of models of the response function. *Vision research*, 19 (4), 401–406.

Jenson, J.R., 2005. *Introductory digital image processing: a remote sensing perspective*. New York: Prentice Hall, 526.

Kleinschmidt, J. and Dowling, J.E., 1975. Intracellular recordings from gecko photoreceptors during light and dark adaptation. *Journal of general physiology*, 66 (5), 617–648.

Korpi-Anttila, J., 2003. *Automatic color enhancement and scene change detection of digital video*. Licentiate thesis. Laboratory of Media Technology, Helsinki University of Technology, Finland, 44–47.

Naka, K.I. and Rushton, W.A., 1966. S-potentials from luminosity units in the retina of fish (cyprinidae). *Journal of physiology*, 185 (3), 587–599.

Pizer, S.M., *et al.*, 1987. Adaptive histogram equalization and its variations. *Computer vision, graphics and image processing*, 39, 355–368.

Smith, M.J.T. and Docef, A., 1999. *A study guide for digital image processing*. Riverdale, GA: Scientific Publishers, 487.

Yu, C.Y., *et al.*, 2009. Contrast adjustment in displaying scenes using inverse hyperbolic function. *In*: *The 22nd IPPR conference on computer vision, graphics, and image processing*, 23–25 August 2009, Nantou, Taiwan, 1020–1027.

Yu, C.Y., *et al.*, 2010a. Adaptive inverse hyperbolic tangent algorithm for dynamic contrast adjustment in displaying scenes. *EURASIP journal on advances in signal processing [online]*, 2010 (485151), 1–20.

Yu, C.Y., *et al.*, 2010b. Two-scale image contrast enhancement based on adaptive inverse hyperbolic tangent algorithm. *In*: *2010 International conference on high-speed circuits design* (*HSCD'10*), 28–29 October 2010, Taichung, Taiwan, 22–29.