Image Contrast Enhancement Using Adaptive Inverse Hyperbolic Tangent Algorithm Based on Image Segmentation by Watershed Technology

[1*]Cheng-Yi Yu and [2]Hsueh-Yi Lin

Abstract

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. In the image enhancement technology, we have proposed local contrast enhancement based on Adaptive Inverse Hyperbolic Tangent Algorithm (AIHT), and, further, the image contrast enhancement algorithms can be adaptively adjusted according to the characteristics of the image. Its image segmentation method is based on "row" or "column" scale oriented. Such benefits can be for different directions of the light source, and select more suitable processing methods to resolve overexposed and underexposed phenomenon. The regional image segmentation to section parameters was adjusted for the region, so that image contrast enhancement can effectively improve the shortcomings of global contrast enhancement. However, the image segmentation method is section parameters to use rows for the selected region size, and bring about unevenly distributed brightness values in the region. As a result, image enhancement will be affected. Therefore, this paper proposes image segmentation by watershed technology, which base brightness values for the selected region size. That result evenly distributes brightness values in the region, which can be applied to the image contrast enhancement process in order to achieve a clearer display quality and contrast enhancement. We also use Adaptive Removing Glare Algorithm to perform noise filter for the original image. That is the pre-processing for image contrast enhancement to achieve a more favorable image enhancement. Experimental results show that the proposed algorithm exhibits the ability to enhance local details while being powerful, and that can take shape using local detail and edge information.

Keywords: Watershed Algorithm, Image Segmentation, Removing Glare Algorithm, Adaptive Inverse Hyperbolic Tangent Algorithm

*Corresponding Author: Cheng-Yi Yu
(E-mail:)
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1. Introduction

In real-world situations, light intensities have a large ranges. Nevertheless, most digital cameras and display devices are only capable of a small ranges [1]. 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. When viewing pictures of outdoor scenes, we can tell whether part of the image is over-exposed or under-exposed because the dynamic range of human vision is much higher than the range of most image sensors. Therefore, the contrast enhancement is a common operation with regard to image processing. Used to improve poor quality images, it is also useful in improving details in photographs which are over or under-exposed.

This paper presents an Adaptive 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 [2] 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.

However, the parameters of this method are obtained by values calculation of the entire image, so we propose a new method to obtain improved parameters; we use the method of image segmentation evaluation luminance value of each region in order to solve the non-uniform distribution of luminance values of the entire image area of the image segmentation phenomenon whose certain parameters are adjusted so that the image contrast enhancement effect has been improved [3].

The remainder of this paper is organized as follows: Section 2 reviews the previous work done in the literature. Section 3 presents the principles of new and improved methods. Section 4 conducts experiments including simulations. Finally, Section 5 provides future directions of further research.

2. Image Segmentation and Image Contrast Enhancement Method

In image enhancement technology, we have proposed local contrast enhancement based on Adaptive Inverse Hyperbolic Tangent Algorithm (AIHT); further, the image contrast enhancement algorithms can be adaptively adjusted according to the characteristics of the image. Its image segmentation method is based on "row" or "column" scale oriented. Such benefits can be for different directions of the light source, and select more suitable processing methods to resolve overexposed and underexposed phenomenon. Through the regional image segmentation to section parameters, it is adjusted for the region; therefore, that image contrast enhancement can effectively improve the shortcomings of global contrast enhancement.

2.1 Image Segmentation Method

Local contrast enhancement is performed by sliding windows across the image and adjusting the center element [4]. This section introduces row and column blocks, where I is the brightness value of the original image; Ixy is the brightness value of the image in point (x,y), where the matrix size has r rows and c columns; image segmentation by row block of the contrast enhancement is r^{th} to be carried up and down in the row to enhance its regional assessment area; image segmentation by column block of the contrast enhancement is c^{th} to be carried up and down in the column to enhance its regional assessment area, in order to assess the regional range of values [5]. Figure 1 is image segmentation by row block diagram explanation; Figure 2 is an image segmentation by column block diagram explanation.

Figure 1: Image Segmentation by row block.

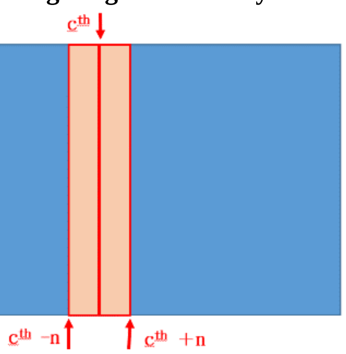

Figure 2: Image Segmentation by column block.

A row (or column)-oriented region serializes all of the pixels in 2n+1 row (or column) together, divides the original image into several sub-blocks, and performs an estimates of enhanced parameter to center row (or column) of each sub-block. The sub-blocks are used as base-row (or column) that is center-row, and up to take the row (or column) and down to take the row (or column). Then it is lack of up or down to take row (or column) to fill it from the other direction.

2.2 Adaptive Inverse Hyperbolic Tangent Algorithm (AIHT)

The AIHT enhancement algorithm is an adaptive adjustment of the Inverse Hyperbolic Tangent (IHT) function determined by each pixel's radiance. The bias(x) and gain(x) parameters control the shape of the IHT function [2]. 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. 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 HSI (hue, saturation, and intensity) method is a common approach used for such color-to-gray-scale conversion. The intensity value is the grayscale component in the HSI color space. The weights reflect the eye's brightness sensitivity to the primary colors. In general, a color image can be converted to a gray scale value. All the gray levels of the original image must be normalized to the range of [0,1] before implementing AIHT. Because this function is an asymptote, the outputs are always bounded between 0 and 1[6]. Another advantage of using this function is that it supports an approximately inverse hyperbolic tangent mapping for intermediate luminance, or luminance distributed between dark and bright values [7,8,9].

Figure 3 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 4 shows a block diagram of AIHT parameters evaluates, including bias(x) and gain(x) parameters.

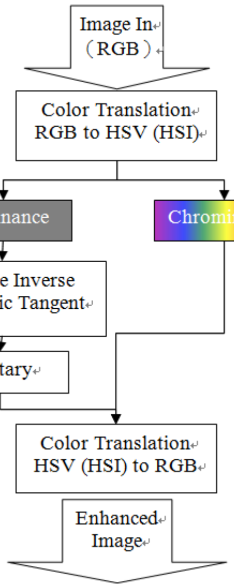

Figure 3. A : Flowchart of the AIHT algorithm.

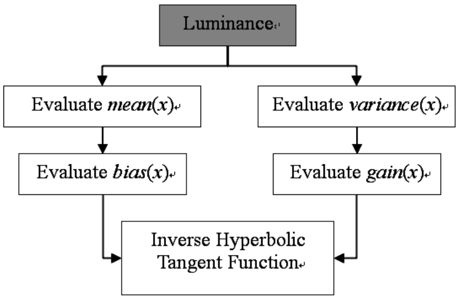

Figure 4. A: flowchart of AIHT parameters evaluates.

A higher gain value means a higher rate in change. 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.

To make the inverse hyperbolic tangent curve produce a smooth mapping, we rely on Perlin and Hoffert "bias" function. 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. 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

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

The gain function determines the steepness of the AIHT curve. 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 midrange of objects in a soft region goes from 0 to 1. A higher gain value means a higher rate in change. The gain function is defined by

$$gain(x)=0.1\times\left(variance(x)\right)^{0.5}=0.1\times\left(\frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x_{ij}-\mu\right)\right)^{0.5} \qquad (2)$$

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

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

$$Enhance\left(x_{ij}\right)=\frac{1}{2}\ln\left(\frac{1+\left(\left(x_{ij}^{bias(x)}-0.5\right)\times 2\times gain(x)\right)}{1-\left(\left(x_{ij}^{bias(x)}-0.5\right)\times 2\times gain(x)\right)}\right) \qquad (3)$$

Inverse Hyperbolic Tangent Curves are produced by varying the gain and bias values: gain(x) parameter fixed and varying the bias(x) parameter are shown in Figure 5; bias(x) parameter fixed and varying the gain(x) parameter are shown in Figure 6. By adjusting the bias(x) and gain(x), it is possible to tailor a remapping function with appropriate amounts of image contrast enhancement.

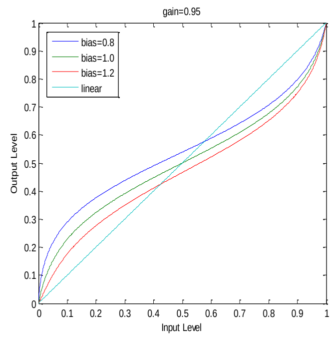

Figure 5: gain(x) parameter fixed and varying the bias(x) parameter.

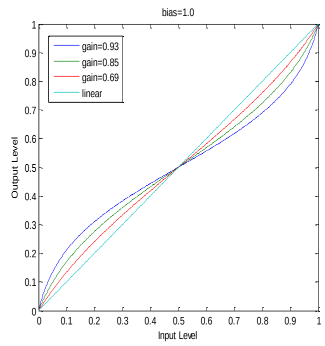

Figure 6: bias(x) parameter fixed and varying the gain(x) parameter.

The AIHT algorithm 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. Another is that the AIHT-based algorithm can only be used for the global contrast enhancement and cannot achieve for a local contrast enhanced. 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. Therefore, it is unable to meet the Human Visual System mapping curve and produce a non-smooth or distorted images phenomenon.

3. Local Image Contrast Enhancement Using AIHT Algorithm Base on Image Segmentation by Watershed Technology

The watershed algorithm [10] is a common image segmentation technology. It converts the image into topographic map to search out all the catchments in the image in the concept of topography.

The principle of watershed algorithm is to obtain the gradient image of an image before using horizontal and vertical coordinates and image gradient value to display the three-dimensional topographic map of gradient image. In terms of topography, for the topographic map of a gradient image, the difference in the gradient value can cause fluctuant terrain, so there are many catchment basins and watersheds between catchment basins. The concept of watershed algorithm is constructed on this topographic map. The watershed algorithm recognition uses the above concept to mark the position with maximum change in image gray-scale value on the image.

The flow sequence of the proposed method is presented in Figure 7. The proposed algorithm processing was done in the HSI color space to enhance images. The light source for the image is presented on the most important part. Therefore, only I components was enhanced, and original hue and saturation were maintained. It was based on the complete preservation of the color information (Hue) of the original image. Initially, the original or normal scale RGB image were converted into Hue-Saturation-Intensity (HSI) color space from HSI space to separate hue and saturation from intensity. The hue and saturation components are preserved to avoid image distortion. Then, the contrast enhancement using AIHT algorithm based on watershed for image segmentation is conducted, which is only aimed at the brightness value of the original image. In image processing, if the image hue and saturation component are changed, the color information of the original image will be distorted.

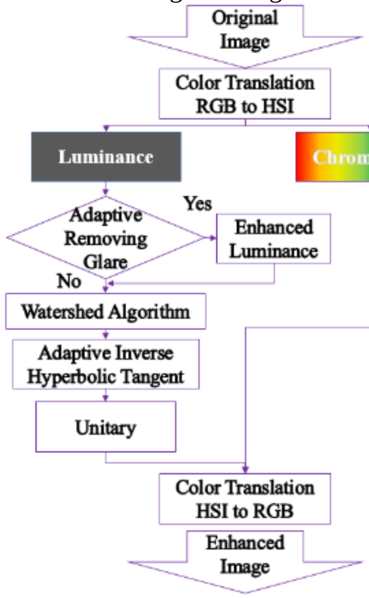

Figure 7: Flowchart of contrast enhancement using AIHT algorithm base on watershed for image segmentation.

The contrast enhancement using AIHT algorithm based on watershed for image segmentation is according to the all pixels' radiance by the watershed algorithm segmented into sub-region. The input data are read, and different region parameters are also generated. Different sub-region parameters can affect the newly generated image shape. There are two important goals for our proposed algorithm 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).

3.1 Adaptive Removing Glare

Glare is any non-image-forming light, which usually occurs when the camera is pointed towards a light source. An image effect caused by glare is the uneven intensity phenomenon. Light can bounce about between the lens elements to create a cascade of bright lens glares. It also causes a general degradation in image saturation and contrast. This section presents the image adaptive removing glare processing.

With the popularity of digital imaging devices and the improvement of imaging equipment performance, higher quality image should cater to people's requirements. Outdoor images are usually degraded in the process of obtaining image, due to the opacity of the media of atmospheric. During the process of atmospheric transmission, light mixes with atmospheric light (surrounding environment reflected light), case images' contrast and color fidelity decline when the scene reaches to the imaging equipment. The degree of the atmospheric scattering is affected by the distance between the scene and the camera, so the image quality is changed along with the change of spatial. [11]

Images of outdoor scenes are usually degraded by the turbid medium (e.g., sun-light, particles, water-droplets) in the atmosphere. Glare, haze and fog are such phenomena due to atmospheric absorption and scattering. He, Sun and Tang describe a procedure for removing haze from a single input image using the dark channel prior. That algorithm analysed the intensity values by the dark channel to implement removing glare. The removing glare algorithm is to solve image over bright problems caused by overexposure.

In computer vision and computer graphics, the model used to describe the formation of an intensity image is:

$$I(x) = J(x)t(x) + A(1 - t(x)) \qquad (4)$$

Where I is the observed intensity; t is the medium transmission describing the portion of the light that is not scattered and reaches the camera; J is the image scene radiance; A is the global atmospheric light. The goal of glare removal is to recover J, A, and t from I. When the atmosphere is homogenous, the transmission t can be expressed as:

$$t(x) = e^{-\beta d(x)} \qquad (5)$$

Where β is the scattering coefficient of the atmosphere, and d is the scene depth. This equation indicates that the scene radiance is attenuated exponentially with the depth. Dark Channel Prior algorithm is divided into four steps: dark channel prior, estimating the transmission, estimating the atmospheric light and recovering the scene radiance.

1) Dark Channel Prior:

This algorithm is based on the observation outdoor scene image: in the non-sky patches, at least one color channel has very low intensity at some pixels. In the minimum intensity anyway, a patch has a very low value express as:

$$J^{dark}(x) = \min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(J^c(y)\right)\right) \qquad (6)$$

2) Estimating the transmission

The image is estimated atmospheric transmittance, and avoids excessive image processing to remove glare and halos and other natural phenomena caused. Equation (9) will be added to the adaptation parameters. The nice property of this modification is that we adaptively keep more glares for the distant objects. The value of $\omega(0 < \omega < 1)$ is application based. We fix it to 0.92 for all results reported in this paper.

$$t(x) = 1 - \omega \min_{y\in\Omega(x)}\left(\min_{c} \frac{I^c(y)}{A^c}\right) \qquad (7)$$

3) Estimating the atmospheric light

Extracting the dark channel of the brightest band of 0.1%, a pixel and their corresponding maximum brightness values in the original image are used as an estimate atmospheric light(A).

4) Recovering the scene radiance

A typical value of scene radiance is 0.1. Since the scene radiance is usually not as bright as the atmospheric light; the image after glare removal looks dim. Therefore, we increase the exposure of J(x) for display. With the transmission map, we can recover the scene radiance according to Equation (7). The final scene radiance J(x) is recovered by:

$$J(x) = \frac{I(x) - A}{\max(t(x), f_x)} + A \qquad (8)$$

But the direct attenuation term J(x)t(x) can be very close to zero when the transmission t(x) is close to zero. The directly recovered scene radiance J is prone to noise. Therefore, we join the transmission t(x) to an adaptive threshold f_x, which means that a small certain amount of glare are preserved in very dense glare regions, and achieve adaptive processing.

3.2Watershed Algorithm:

The watersheds concept is one of the classic tools in the field of topography. It is the line that determines where a drop of water will fall into particular region. In mathematical morphology, gray-scale images are considered as topographic relieves. The watershed transform is a morphological based tool for image segmentation [12].

In grey scale the mathematical morphology watershed transform for segmentation was originally proposed by Digabel and Lantuejoul in 1977, and later improved by Li et Al in 2003[13]. As shown in Figure 8, the watershed transform can be classified as a region-based segmentation approach. The watershed transform finds catchment basins CB and watershed ridge lines in an image by treating it as a surface where light pixels are high and dark pixels are low. Image data may be interpreted as a topographic surface where the gradient image gray-levels represent altitudes.

Raw watershed segmentation produces a severely over segmented image with hundreds or thousands of catchment basins. To overcome this problem, we used region markers to generate good segmentation. The marker-controlled watershed segmentation has been shown to be a robust and flexible method for segmentation of objects with closed contours, where the boundaries are expressed as ridges. The marker image used for watershed segmentation is a binary image consisting of either single marker points or larger marker regions, where each connected marker is placed inside an object of interest. Each initial marker has a one-to-one relationship to a specific watershed region, so the number of markers will be equal to the final number of watershed regions. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbours.

We used region markers to generate segmentation, and then this paper presents an Adaptive Inverse Hyperbolic Tangent (AIHT) algorithm for image contrast enhancement.

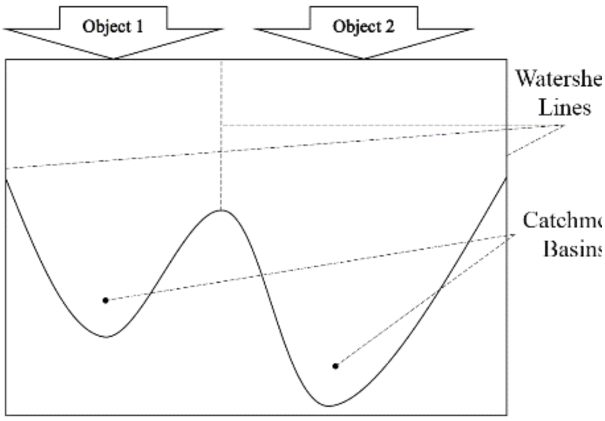

Figure 8: Watershed Algorithm.

Finally, the new contrast enhanced brightness value I, with the original value of hue (H), saturation (S), and then back to RGB color space combined value through the color space conversion function, we will get a new image after contrast enhancement.

4. Experimental Results and Discussions

In order to compare the image enhancement techniques, the comparison of images before and after enhancement is needed. In this section, experiments are conducted in order to compare the performances of common image enhancement algorithms in terms of their processing capacities and enhanced image visual quality with those proposed algorithms. The experiments use overexposed and underexposed images caused by an ambient light source. This study conducts the experiment with three common image contrast enhancement algorithms: the adaptive inverse hyperbolic tangent algorithm, adaptive local inverse hyperbolic tangent algorithm based on image segmentation by row block and column block, respectively. It then compares their performances with those of the proposed algorithm in this paper, and it was added to executed analysis of the presence or absence by Adaptive Removing Glare(ARG) algorithm. Compared as shown in Figures 9, (a) is the original image; (b) is the result processed with AIHT algorithm; (c) is the result processed with AIHT algorithm after ARG algorithm; (d) is the result processed with AIHT algorithm based on image segmentation by row block(n=4); (e) is the result processed with AIHT algorithm based on image segmentation by row block after ARG algorithm(n=4); (f) is the result processed with AIHT algorithm based on image segmentation by column block(n=4); (g) is the result processed with AIHT algorithm based on image segmentation by column block after ARG Algorithm(n=4); (h) is the result processed with the proposed algorithm in this paper; (i) is the result processed with the proposed algorithm in this paper after ARG algorithm.

In subjective analysis, the visual quality of an image is evaluated with the visual feeling of human eyes as the benchmark. As shown in Figures 9, the Adaptive Inverse Hyperbolic Tangent image enhancement algorithm was used to estimate parameters value of the entire image. Therefore, that is fast and simple, and is suitable for overall enhancement of the image. This fact limits the contrast ratio in some parts of the image and hence causes significant contrast losses in the background and other small regions. This technique cannot be adapted to local brightness features of the input image because only global histogram information over the whole image is used. Then, the Adaptive Local Inverse Hyperbolic Tangent algorithm is applied to improve or enhance the local image quality and amount in much details and color information of image. However, it's not to solve the unevenness problems of uneven illumination phenomenon. The proposed image enhancement method added to adaptive glare-removal processing systems yields good results in enhancing degraded images with most gray levels and low contrasts. The proposed enhancement methods also yield better results than those offered by traditional image enhancement techniques.

Aimed at the processing result of the four above algorithms, in objective analysis, this study uses four image quality evaluation methods to evaluate the quality of the image processed by the four objective analysis: Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Normalized Absolute Mean Brightness Error ($AMBE_N$), and Structure Similarity Index Measure(SSIM) [14][15].

MSE is used to evaluate the difference between the original image and the enhanced image, where the smaller MSE represents a smaller difference between the enhanced image and original image, and shows better image visual quality. PSNR is the ratio between the maximum value of the image signal and the noise in the image. The larger ratio represents more approximation of the enhanced image to the original image, and shows better visual effect of image quality. $AMBE_N$ is defined as the absolute difference of the mean intensity between the original and the contrast enhanced images. If $AMBE_N$ is small, the average brightness of the image is well preserved. SSIM is a digital image to measure the similarity of two indicators. The structural similarity between the two can be seen as image quality distortion measure; if the value of the structural similarity index is greater, representing the two images of similarity is higher. This study evaluates the image processed with the four algorithms, respectively, and the evaluation result is shown in Table 1. From the above discussion and experimental results, it can be concluded that the proposed algorithm produces better results, and is a simple technique. As shown in Table 1, while Adaptive Local Inverse Hyperbolic Tangent algorithm through region segmentation have to adjust the parameters of the area, it is still subject to the luminance distribution within the image area which can't be caused by uneven image showed good quality. Although this method has three types of images for the image to achieve enhanced range, within the region it will still be the brightness of the image caused by the uneven distribution of the image, so it can't display better quality.

According to the above data, it can be learned, in this paper, the proposes algorithm method is not only against overexposure and underexposure of the image adaptive image enhancement, and by parameter adjustment region it will not be the case of image brightness unevenly distributed which leads to poor image rendering; more details show more regional information enhanced to achieve better results.

In this paper, the equipment used for executed Effectiveness Evaluation is : PC Intel i5 2.8G, 8.0 GB RAM,Windows 7, Matlab R2014a.

5. Conclusions

The Adaptive Local Inverse Hyperbolic Tangent algorithm can process various types of image artifacts which are caused by external light sources. It can effectively supplement the brightness value for the area with insufficient information, so it presents a clear visual effect for an underexposed image without causing the phenomenon of excessive distortion due to excessive image enhancement.

In this paper, the proposed method can smoothly enhance an image without excessively enhancing the image. On the whole, the proposed method of regions classification effectively improved the original use of "row" or "column" image region segmentation. The adjustment value of enhancement parameters was limited by the regional differences of image brightness. The results affect the quality of the image, and it can be classified according to the brightness of the image property. The proposed techniques can enhance overall contrast more effectively, and it makes good use of local information. The algorithm proposed in this paper can judge the exposure degree based on image brightness distribution, thus adaptively enhancing the image. In addition, because it conforms to the original characteristics of the image and enhances it, the image can present more detailed information.

Acknowledgment

This work was supported by the Ministry of Science and Technology of Taiwan, under the Grant No. MOST 104-2221-E-167-029-.

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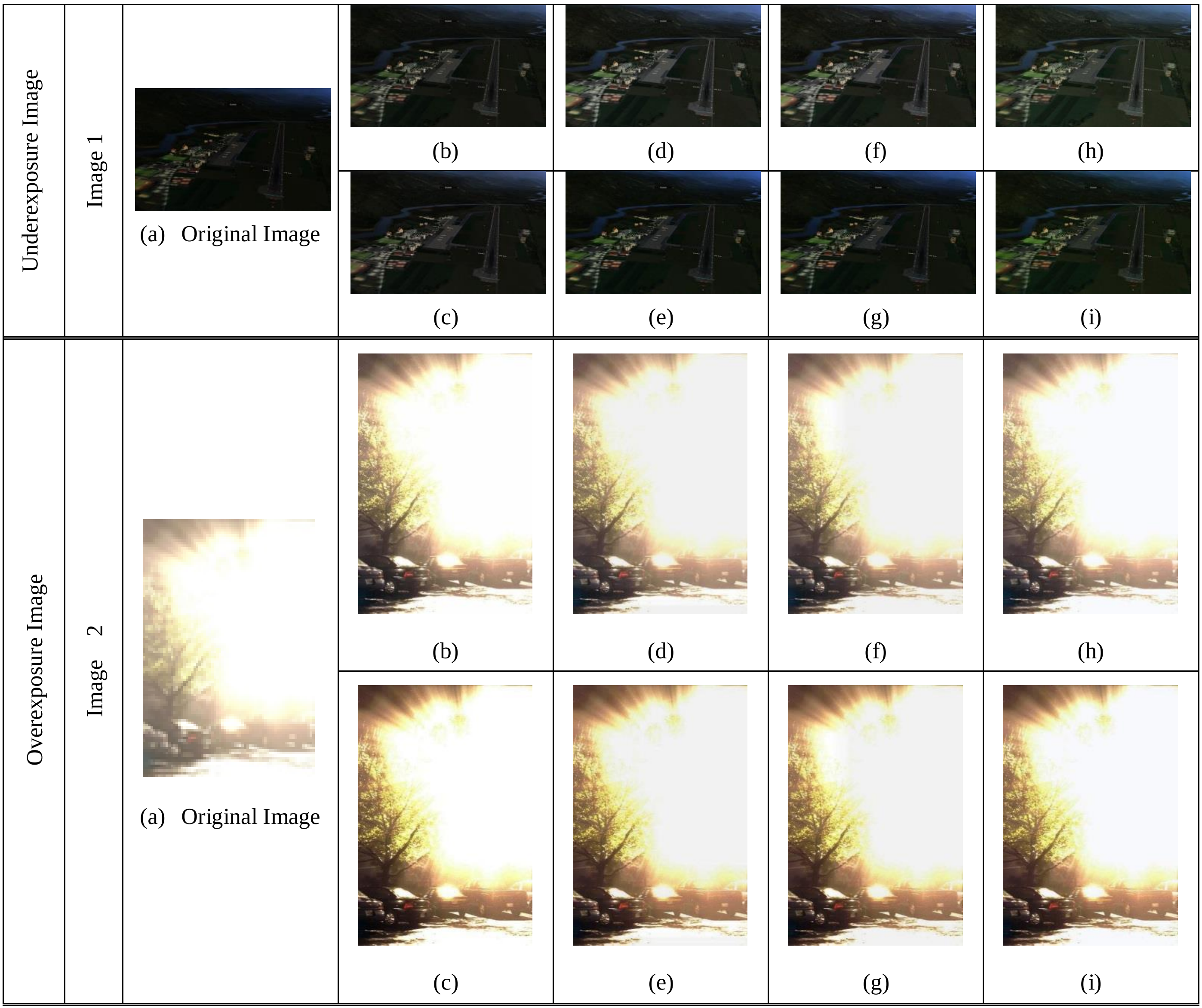
Table 1. MSE, PSNR, $AMBE_N$, SSIM, TIME image quality evaluation and comparison.

Image	Method	MSE	PSNR	$AMBE_N$	SSIM	TIME(s)
Image 1	AIHT	0.00004	91.8192	1.0051	0.9985	0.4973
	ARG_AIHT	0.00002	95.3322	1.0033	0.9986	2.4802
	AIHT Row block (n=4)	0.00319	73.0921	1.0480	0.9116	0.9187
	ARG_AIHT Row block (n=4)	0.00171	75.7985	1.0324	0.9141	2.9241
	AIHT Column block (n=4)	0.00332	72.9625	1.0484	0.9113	1.0388
	ARG_AIHT Column block (n=4)	0.00174	75.8047	1.0324	0.91423	3.0411
	Proposed WAIHT	0.00657	69.9586	1.0761	0.8073	1.6012
	Proposed ARG_WAIHT	0.00451	71.5514	1.0582	0.7924	3.0823
Image 2	AIHT	0.0006	80.4427	1.0156	0.99647	0.0967
	ARG_AIHT	0.0008	79.2175	1.0186	0.9935	0.5162
	AIHT Row block (n=4)	0.0017	75.7012	1.0387	0.9974	0.1851
	ARG_AIHT Row block (n=4)	0.0016	76.0353	1.0355	0.9969	0.6094

	AIHT Column block (n=4)	0.0016	75.8706	1.0386	0.9982	0.1709
	ARG_AIHT Column block (n=4)	0.0016	76.1202	1.0366	0.9981	0.5846
	Proposed WAIHT	0.0001	89.7855	1.0031	0.99947	0.3360
	Proposed ARG_WAIHT	0.0001	86.8303	1.0023	0.9989	0.7536
Image 3	AIHT	0.0001	88.8884	1.0083	0.9993	0.05312
	ARG_AIHT	0.0001	85.1938	1.0118	0.9984	0.2985
	AIHT Row block (n=4)	0.0003	83.4567	1.0033	0.9926	0.1165
	ARG_AIHT Row block (n=4)	0.0002	85.4132	1.0092	0.9966	0.3364
	AIHT Column block (n=4)	0.0002	86.1819	1.0036	0.9975	0.1183
	ARG_AIHT Column block (n=4)	0.0002	85.5119	1.0103	0.9979	0.3488
	Proposed WAIHT	0.0013	76.8945	1.0249	0.9779	0.2502
	Proposed ARG_WAIHT	0.0024	74.3372	1.0361	0.9435	0.4421



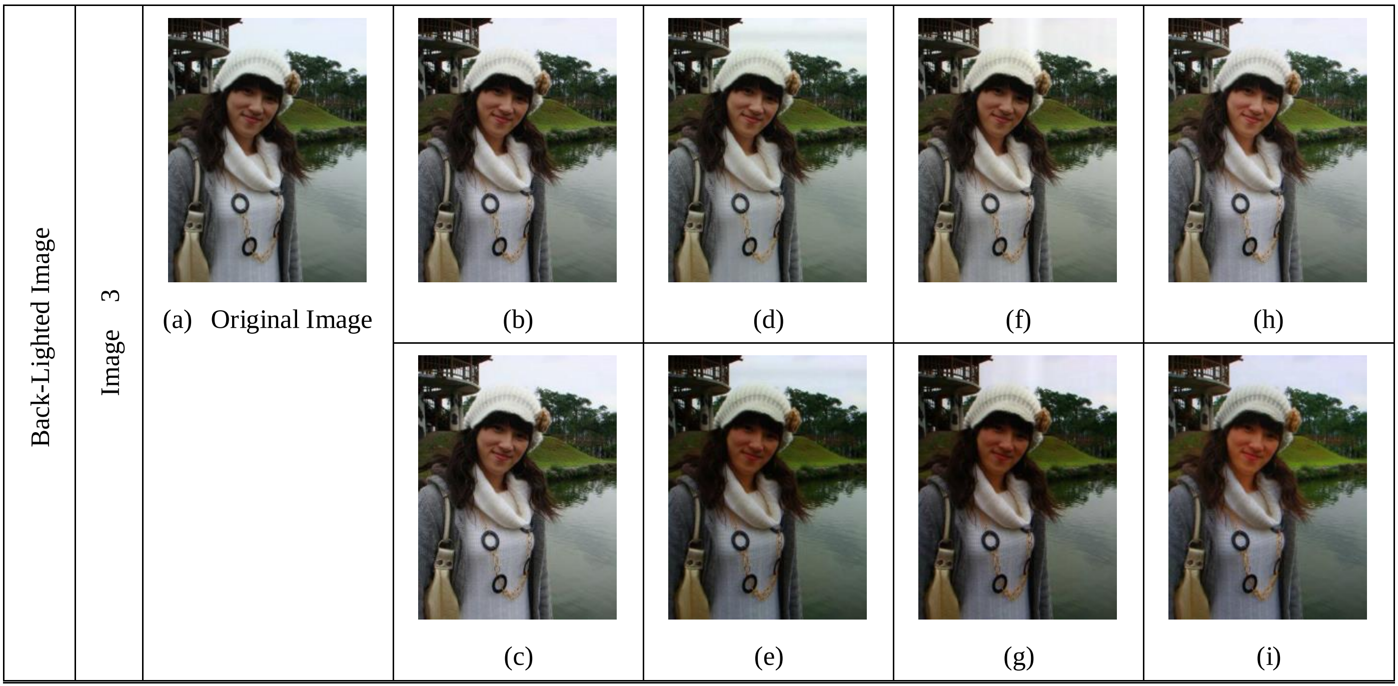


Figure 9: Various types of bad contrast images illustrating the difference between various contrast enhancement algorithm.