Histogram Enhancement Using Adaptive Segmentation Algorithm

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Abstract

An image enhancement algorithm based on adaptive segmentation for image contrast enhancement is presented. In this study, an automatic adaptive segmentation histogram enhancement (ASHE), based on discriminant analysis, is utilized to recursively segment an image into several clusters first. After segmentation, different object and background components are segmented into separate clusters, called object planes. Then, the dynamic range of each object plane is adjusted according to its visual characteristics. Finally, each object plane is enhanced within the new dynamic range respectively. Because the proposed algorithm can automatically segment an image into different object planes and enhance the image according to the visual characteristic of each object plane, each object and background components of the image can be well enhanced. Experimental results for poor-contrast images and the comparisons for some of the previous studies are provided to demonstrate the robustness, visual quality, and effectiveness of the proposed algorithm.

1. Introduction

Enhancement is a common technique in today's digital products. It not only intensifies the vision identities but also shows the indistinct information of an image. One of the most popular enhancement algorithms is the histogram equalization (HE) [1]. The HE can redistribute the histogram such that the enhanced image has better contrast than the original image. Because the traditional HE is a global operation algorithm, the image enhanced by the traditional HE does not preserve the image brightness and may cause the enhanced image over darkness or over lightness. Therefore, the HE is not being suggested to be used directly for the applications in consumer electronics.

There are some enhancement algorithms which based on the HE to improve the image quality. Noor *etc.* [2] presented adaptive histogram equalization (AHE) for suspected fish bone ingestion on the lateral neck radiograph. The AHE split the radiograph into different block sizes, and then using the HE in the multiple block size area to emphasize the local contrast. Rajavel [3] proposed image-dependent brightness-preserving histogram equalization (IDBPHE) to enhance images and preserve the brightness simultaneously. The IDBPHE use the wrapping discrete curvelet transforms to identify bright regions of an original image, and modify the histogram of the original image with respect to the histogram of the identified regions.

In 1997, Kim [4] proposed brightness preserving bi-histogram equalization (BBHE). The method uses the mean value of the image histogram to divide the histogram into two sub-histograms, and then equalizes the sub-histograms independently. However, dividing the histogram into two sub-histograms is still not enough to enhance the images with complex foreground/background. Hence, some researchers proposed different algorithms to divide the histogram into more than two sub-histograms. Ibrahim *etc.* [5] divided an image into several sub-regions by grouping the pixels based on the smoothed value processed by Gaussian filter. According to each sub-region, the enhanced image is obtained using the average values processed by HE for the original and negative images. Yang and Wu [6] proposed multiple-peak images based on Histogram equalization (MPIBHE). The MPIBHE convolves input image with a Gaussian filter, and then divides the original histogram into different partitions by the valley values of the histogram. Finally, each partition is enhanced by the proposed enhancement method. Lin *etc.* [7] proposed static-separate tri-histogram equalization (SSTHE) to split the image histogram into three sub-regions by the mean and standard deviation of the image.

Combining the valley values and the mean and standard deviation of the image histogram, Abdullah-Al-Wadud *etc.* [8][9] proposed dynamic histogram equalization (DHE). The DHE partitions the image histogram based on the valley values and splits the sub-histogram for not having normal distribution. To replace the valley values with the peak values, Ibrahim *etc.* [10] presented brightness preserving dynamic histogram equalization (BPDHE) to partition the image histogram based on the local maximums/peak values, and then assigned each partition to a new dynamic range. Park *etc.* [11] proposed dynamic range separate histogram equalization (DRSHE) to equally separate the range of histogram into k sub-histograms, k set 4 in the study, and resized each dynamic range based on its area ratio. Then DRSHE uniformly redistributed the intensities of histogram in each new dynamic range.

These previous studies proposed different segmentation algorithms to solve the problems of HE. As the previous studies show the histogram segmentation algorithm influences the visual quality. Therefore, this study proposes a new algorithm named adaptive segmentation histogram enhancement (ASHE) to segment the image histogram according the classification of the gray-values of the image. The ASHE segments image histogram based on discriminant analysis, and resizes the dynamic range of each cluster according to the statistic features of the sub-region. Then ASHE enhances each cluster with HE algorithm. The experimental results of ASHE are compared with the results of the HE, BPDHE, DHE, and DRSHE

2. The Adaptive Segmentation Histogram Enhancement

The adaptive segmentation histogram enhancement (ASHE) contains three steps. The first step is an automatic segmentation algorithm based on discriminant analysis. The segmentation algorithm can segment the histogram of an image into different clusters according to the classification of the gray-values of the processed image automatically. After the segmentation algorithm, different object and background components are segmented into separate clusters, called object planes. The next step maps the dynamic range of the gray-values of each cluster into a new one. The new dynamic range is adjusted by the visual characteristics of each cluster. The final step enhances the contrasts of each cluster with the new dynamic range respectively. The details of the steps are described as following.

The first step of ASHE is the automatic segmentation algorithm. In this subsection, an automatic segmentation algorithm is introduced to segment images. The algorithm is an unsupervised and automatic one to partition the image from the histogram information. For a given gray image Y, the pixels of Y can be partitioned into suitable number of clusters, automatically. For k clusters, pixels of Y are segmented by applying k-1 thresholds – $T_1,\ldots, T_n, \ldots, T_{k-1}$. These clusters are represented by $S_0= \{X, X+1,\ldots, T_1\}$,…, $S_n= \{T_n+1, T_n+2,\ldots, T_{n+1}\}$,…, $S_{k-1}= \{T_{k-1}+1, T_{k-1}+2,\ldots, L-1\}$, where the range of gray-values is defined within $[X, L-1]$. Based on the discriminant analysis [12], the between-class variance v_{BC} is defined as,

$$v_{BC} = w_0(\mu_0-\mu_G)^2 + \ldots + w_n(\mu_n-\mu_G)^2 + \ldots + w_{k-1}(\mu_{k-1}-\mu_G)^2 \quad (1)$$

where $w_0,\ldots, w_n,\ldots, w_{k-1}$ denotes the class-probabilities for the clusters $S_0,\ldots, S_n,\ldots, S_{k-1}$, respectively; μ_G denotes the global mean value of the image Y; $\mu_0,\ldots, \mu_n,\ldots, \mu_{k-1}$ denotes the mean values of the clusters $S_0,\ldots, S_n,\ldots, S_{k-1}$, respectively. And, they are defined as

$$w_0 = \sum_{i=X}^{T_1} p(i) ,\ldots, w_n = \sum_{i=T_n+1}^{T_{n+1}} p(i) ,\ldots, w_{k-1} = \sum_{i=T_{k-1}+1}^{L-1} p(i) , \quad (2)$$

$$\mu_0 = \frac{\sum_{i=X}^{T_1} ip(i)}{w_0} ,\ldots, \mu_n = \frac{\sum_{i=T_n+1}^{T_{n+1}} ip(i)}{w_n} ,\ldots, \mu_{k-1} = \frac{\sum_{i=T_{k-1}+1}^{L-1} ip(i)}{w_{k-1}} , \quad (3)$$

$$p(i) = \frac{h(i)}{N} , \text{ and } \mu_G = \sum_{i=X}^{L-1} ip(i) , \quad (4)$$

where $h(i)$ is the histogram of the gray-value i, N is the total pixels of Y, and $p(i)$ is the probability of gray-value i. Equation (1) yields a measure of discriminant of all existing clusters decomposed from Y, denoted by the "discriminant factor" - DF, and is defined as,

$$DF = \frac{v_{BC}}{v_G} , \text{ where } v_G = \sum_{i=X}^{L-1} (i-\mu_G)^2 p(i) . \quad (5)$$

The v_G is the global variance of the gray values of the image Y. The DF value measures the separability among all existing sections decomposed from the image Y. The DF value is within the range $0 \le DF \le 1$. Maximizing the DF value can optimize the partition result. The details of the proposed algorithm are presented below.

Step 1. For a given gray image Y, determine the standard deviation - σ_0 ; initially, there is only one cluster S_0; If $\sigma_0 > TH_\sigma$, perform the following steps; otherwise, do not process Y and then go to step 6.

Step 2. Currently, there are q clusters exist, which have been decomposed from Y. Compute the histogram, the class-mean μ_n, the class-probability w_n, and the standard deviation σ_n , of each existing class S_n decomposed from Y.

Step 3. From all clusters S_n, determine the cluster S_p with the maximum standard deviation $\sigma_{\max}$, which is to be partitioned in the following step to achieve maximal increment of DF .

Step 4. Partition S_p: $\{T_p+1, T_p+2,\ldots, T_{p+1}\}$ into two clusters S_{p0} and S_{p1}, by applying the optimal threshold T_S^* : S_{p0}: $\{T_p+1, T_p+2,\ldots, T_S^*\}$, and S_{p1}: $\{T_S^*+1, T_S^*+2,\ldots, T_{p+1}\}$. The T_S^* is the threshold-value determined by maximizing the between-class variance v_{BC}. Based on the aforementioned definitions, the v_{BC} is defined as Eq. (1).

Step 5. Step 4 yields $q+1$ clusters, $S_0, S_1\ldots, S_q$. Then, DF of all classes is computed using Eq. (5). If $DF < TH_{DF}$, then let $q = q+1$ and go back to step 2; otherwise, go to step 6.

Step 6. Terminate the segmentation process and record all of the partitioned clusters.

This study employs TH_{DF} = 0.9, TH_σ = 10. They are determined from the training using numerous image samples, such that all existing clusters/objects are almost completely separated. Consequently, all objects are recursively segmented into individual partitioned images.

The second step adjusts the dynamic range of the gray-values of each cluster into a new one. The new dynamic range is adjusted according to the visual characteristics of each cluster. After the automatic segmentation algorithm, we can get k clusters segmented by applying k-1 thresholds – $T_1,\ldots, T_n, \ldots, T_{k-1}$. These clusters are represented by $S_0 = \{X, X+1,\ldots, T_1\}$,…, $S_n = \{T_n+1, T_n+2,\ldots, T_{n+1}\}$,…, $S_{k-1} = \{T_{k-1}+1, T_{k-1}+2,\ldots, L-1\}$, where the range of gray-values is defined within $[X, L-1]$. To take account of the visual characteristics, we define an adjustment coefficient Wf_n for S_n as

$$Wf_n = \frac{\mu_n \cdot RS_n}{\sigma_n} , \quad (6)$$

where μ_n and σ_n are the mean and standard deviation of S_n, and the RS_n is the dynamic range of the gray-values in S_n. For the human visual system, because the discrimination in the bright image is better than it in the dark image, the bright image needs more dynamic range than the dark image. And, the standard deviation represents the contrastive degree of a cluster. The smaller of the standard deviation, the wider dynamic range should be distributed. Therefore, the adjustment coefficient is directly proportion to the μ_n and inverse proportion to the σ_n to obtain the better visual quality. The new dynamic range, $RS_n^{'}$, of S_n is defined as

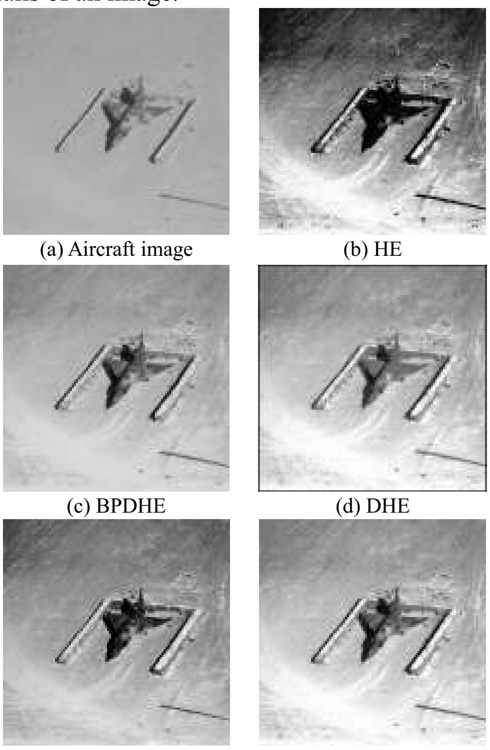
$$RS_n^{'} = RS_n + FS \times \frac{Wf_n}{\sum_{n=0}^{k-1} Wf_n} , \quad (7)$$

where the FS is free space of the image histogram. The free space is the total number of the gray-values that the image does not use. Finally, each cluster is enhanced within the new dynamic range by HE, respectively.

3. Experimental Results

In this study, test images with poor contrast are used to verify the practicability and the stability of ASHE. Also, the comparisons for some of the previous studies are provided to demonstrate the robustness, visual quality, and effectiveness of the proposed algorithm. Four previous algorithms, HE, BPDHE, DHE, and DRSHE, are selected to compare the enhanced images with the results of proposed algorithm. The experiment results are shown from Fig. 1 to Fig. 4. For each figure, the figure (a) is the original image, and the arrangements from figure (b) to figure (f) are the enhanced images of HE, BPDHE, DHE, DRSHE, and the proposed algorithm ASHE.

For the Fig. 1 (a), we can find most of the gray-values are located on the brightness range and the contrast is insufficient. Figure 1 (b) shows the result of the HE. Obviously, the enhanced image of the HE is excessive contrast enhancement, which in turn gives the processed image an unnatural look and creates visual artifacts. From Fig. 1 (c)~(e), we can find the enhanced images processed by the BPDHE, DHE, and DRSHE can improve the drawback of the HE. The Figure 1 (f) shows the result of the proposed ASHE. Because the ASHE can enhance the contrast for each object in the image, ASHE can preserve the details of an image.



(a) Aircraft image (b) HE

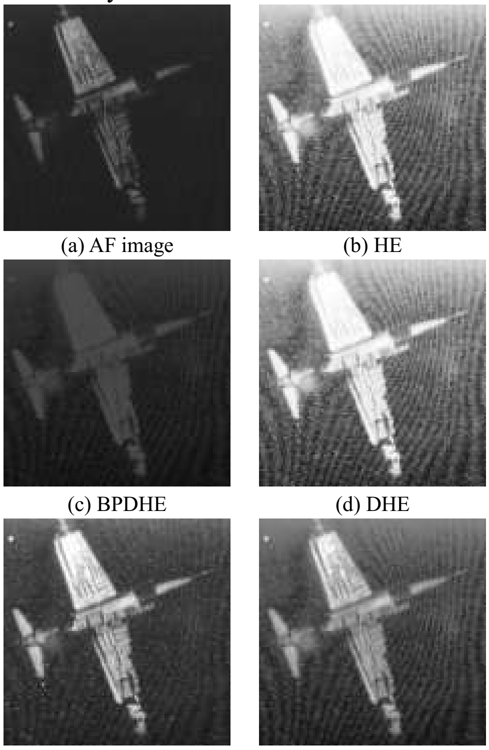
(c) BPDHE (d) DHE

(e) DRSHE (f) ASHE

Fig. 1 Aircraft image and the processed results

Figure 2 (a) is the AF image and the image is too dark to identify the details. From Fig. 2 (b) and Fig. 2 (d), the background of the AF image can be enhanced by the HE and DHE. However, the airplane in the AF image is excessive contrast enhancement. For the processed result of the BPDHE, shown in Fig. 2 (c), the contrast cannot be enhanced appropriately. After processed by the DRSHE and ASHE, the features of the foreground and background can be enhanced clearly. The ASHE still can supply more plentiful detail information.

The Fig. 1 and Fig. 2 are the images with the features of too bright or too dark. In the Fig. 3(a), the Dusk image can be classified to two parts, foreground and background. The background contains the sky and the illumination of the background is passably. However, the contrast and illumination of the foreground containing the building and trees are very bad.



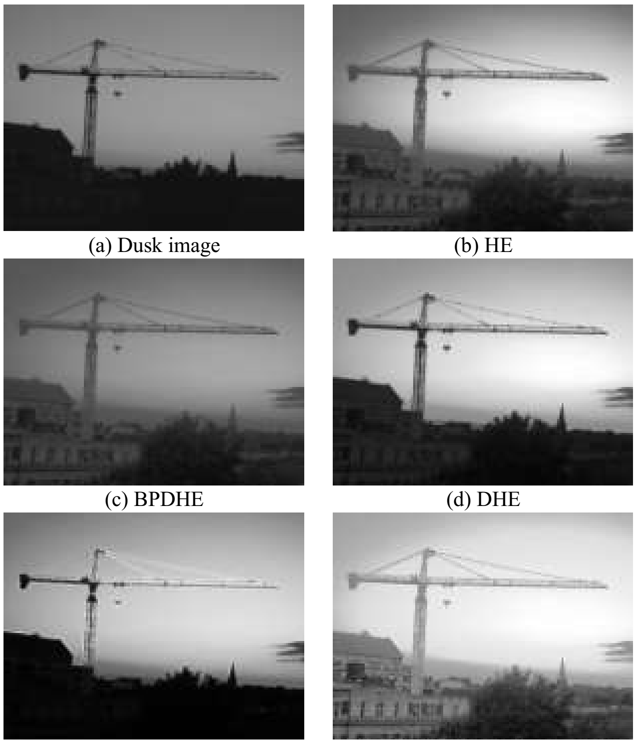
(a) AF image (b) HE

(c) BPDHE (d) DHE

(e) DRSHE (f) ASHE

Fig. 2 AF image and the processed results

After the contrast enhancement of the HE, BPDHE, or DHE, the contrast of the foreground/building can be enhanced, but it is not very clear, shown in Fig. 3 (b)~(d). And, the Fig. 3 (e) shows the DRSHE is not suitable to enhance the image. In the Fig. 3 (f), the ASHE can still enhance the detail information in the foreground/building and the background/sky very clear.



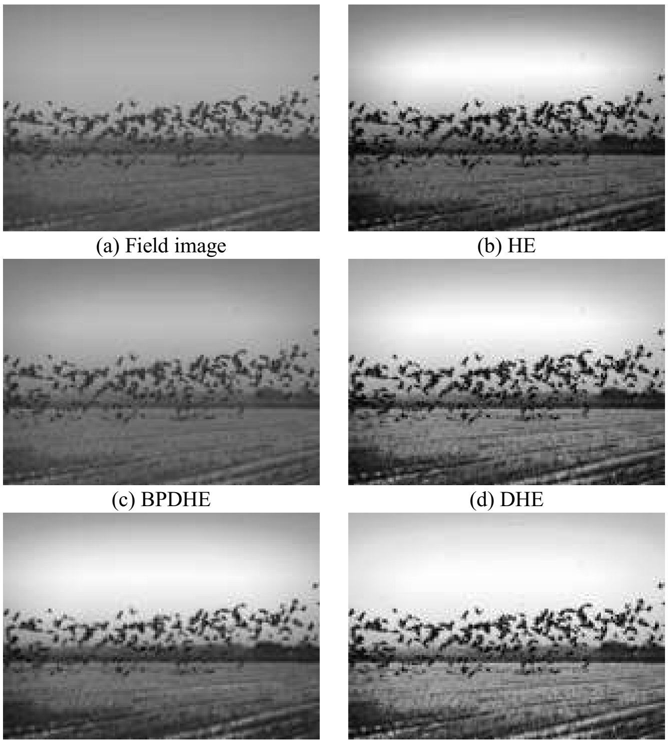
(a) Dusk image (b) HE

(c) BPDHE (d) DHE

(e) DRSHE (f) ASHE

Fig. 3 Dusk image and the processed results

For the Fig. 4(a), the foreground focus on the birds and the field and sky belong to the background. For the results of the HE, DHE, and DRSHE, shown in the Fig. 4(b)(d)(e), these algorithms cannot enhance the foreground and the background simultaneously. And, the Fig. 4(c) shows the BPDHE is not suitable to enhance the image. In the Fig. 4(f), the ASHE can still enhance the detail information in the foreground and the background appropriately.



(a) Field image (b) HE

(c) BPDHE (d) DHE

(e) DRSHE (f) ASHE

Fig. 4 Field image and the processed results

According to the experiment results, we can find the proposed ASHE can enhance the image under different kinds of images and obtain better visual quality than the algorithms of HE, BPDHE, DHE, and DRSHE.

4. Conclusions

This study proposed an automatic adaptive segmentation histogram enhancement (ASHE) algorithm to enhance the contrast of images. The ASHE based on discriminant analysis can automatically segment an image into several clusters according to the distribution of the image histogram. After the segmentation, different foreground and background components are segmented into separate clusters, called object planes. Then, each object plane is respectively enhanced within the new dynamic range adjusted by the visual characteristics of each object plane. Because the proposed algorithm can automatically segment an image into different object planes and enhance the image according to the visual characteristic of each object plane, each object and background components of the image can be well enhanced. In the experimental results, four test images with different poor-contrast problems are enhanced by the ASHE and four famous algorithms of previous studies. And, the ASHE demonstrates the robustness, visual quality, and effectiveness.

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