Local Histogram Equalization Based on OTSU

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Abstract. Histogram equalization is a precondition for an accurate extraction of image features. This paper is to find an appropriate image enhancement method for images with bad contrast features and small target regions. In two different application cases, by analyzing and comparing the results and gray value features, three local histogram equalization methods based on gray segment are evaluated. The local histogram equalization method based on OTSU is then proved to be good in considering its property of emphasizing details while ensuring the overall image’s uniformity.

Introduction

Machine Vision is mainly to extract certain features of an image in order to identify some elements, which belongs to the category of Digital Pattern Recognition [1]. Image enhancement, as one important component of image processing, is the basis and precondition of image features’ extraction and recognition. The purpose of image enhancement is to distinguish target elements from an image and to enhance its contrast, with the distortion to a certain degree.

Histogram equalization (HE), as a spatial domain method, is one of the most commonly used image enhancement method [2, 3]. Traditionally, HE refers to the global histogram equalization which helps equalize the distribution of an image’s gray values. However, it has a disadvantage: small target elements cannot be enough emphasized or even weakened by this method, and it can easily cause an excessive enhancement problem [4]. Confronting this problem, people proposed local histogram methods: Victor and Gregory [5] proposed Adaptive Histogram Equalization, Kim [6] proposed BBHE method based on gray-mean segment, Caselles, Lisani, Morel and Sapiro [7] proposed shape-preserving local contrast enhancement method and etc.

Referring to those methods above, this paper compares the performance of different local HE methods which were based on gray segment in two difference application cases. The following contents: in Section 2, the introduction of the application background and those local HE methods; in Section 3 and 4, based on Section 2, two application cases are illustrated.

Local Histogram Equalization

Definition of the Application Background

This paper compares those local HE methods in the situation as follows:

1) The contrast of the image is bad, which can be divided by two situations: firstly, there’s uneven or not enough illumination; secondly, the image itself is almost mono-color.
(2) The target elements to be extracted are small and the quantity can be one or more.
(3) The image is single-valued, still and digital. Single-valued image, which is also known as gray image, has only one gray value for a picture element (pixel):

\[ g(x, y) = \{s_1(x, y), s_2(x, y), \ldots, s_n(x, y)\}, \text{ where } (x, y) \in \Omega, \]  

Where \(\Omega\) represents the overall region of the given image, \(s_n(x,y)\) is the nth channel’s gray value for a pixel positioned in \((x,y)\) and \(g(x,y)\) is a set of all \(s_n(x,y)\). Note that here \(n=1\).

As about the process of the image processing, the widely accepted view is that image processing can be divided into three steps [4]. This paper extends this three-layer model based on the given application conditions above:

![Image Processing Diagram](image)

Figure 1. Process of image processing.

The image enhancement is the main topic of this paper. In the second step, the “Big” segment is to locate the target element(s) while the “Small” segment is to extract image features from located region(s). As said above, the image enhancement has two objectives: to help do the “Big” and “Small” segment. The following contents focus preferentially on the “Big” segment so the distortion to a certain degree is permitted.

**Local Histogram Equalization Based On Gray Segment**

Let the smallest gray value of a given image as \(G_{\text{min}}\), the largest as \(G_{\text{max}}\), so:

\[ G_{\text{min}} \leq g(i) \leq G_{\text{max}} \]  

Where \(g(i)\), as is defined in Eq.1, is a gray value, while \(i\) represents the gray level, \(i = 0, 1, 2, \ldots, I-1\) (the image has I discrete gray levels denoted as \(g(i)\)). For a given image, the total number of pixels is \(N\), its gray probability density function \(p_i\):

\[ p_i = \frac{n_i}{N}, \]  

where \(n_i\) represents the number of pixels whose gray values are \(g(i)\). Different from the global HE method [8], the local HE method uses a gray threshold value \(B\) to decompose a given image into two sub-images \(\Omega'\) and \(\Omega''\):

\[ \Omega' := \{(x, y), G_{\text{min}} \leq g(x, y) < b\}, \quad \Omega'' := \{(x, y), b \leq g(x, y) \leq G_{\text{max}}\}, \]  

\[ \Omega' \cap \Omega'' = \phi, \ \Omega' \cup \Omega'' = \Omega. \]  

(5)

Let \( b \) represent the level of \( B \), \( N' \) be the total pixel number of sub-image \( \Omega' \) and \( N'' \) be the total pixel number of sub-image \( \Omega'' \), \( N'+N''=N \). Note that in this paper the gray value range of \( \Omega \) equals the equalized gray value range by definition, \( b=B \). The gray probability density functions of these two sub-images are:

\[ \Omega' : p_i = \frac{1}{\Lambda}, \quad i = 0, 1, 2, \Lambda, \quad -1, \]  

\[ \Omega'' : p_i = \frac{1}{\Lambda}, \quad i = 0, 1, 2, \Lambda, \quad -1. \]  

(6) (7)

Suppose that the target elements \( T \) are in the brighter region in view of the whole image, \( T \subset \Omega'' \). Do the HE only for \( \Omega'' \), the cumulative density function \( c(j) \):

\[ (c) = \sum_{i=0}^{j}, \quad i = 0, 1, 2, \Lambda, \quad -1. \]  

(8)

Let \( \text{Gmin}' \) denote the minimum gray value of the transformed sub-image and \( \text{Gmax}' \) denote the maximum gray value of the transformed sub-image. The transform function:

\[ (c) = (\text{\text{Gmax}'} - \text{\text{Gmin}'})* (c) + \text{\text{Gmin}’}. \]  

(9)

Note that \( \text{Gmin}'=0 \) and \( \text{Gmax}'=255 \) by definition. \( B \) can be three values: (1) A gray segment value based on OTSU [8] method; (2) The mean gray value of the given image \( \Omega \); (3) The medium gray value in the transformed gray range, here the medium gray value equals 128.

**Assessment And Comparison**

In the following two application cases, the assessment of those HE methods consists of two: the output images with gray histograms are compared; and two first-order and two second-order gray value features [9] are also used as follows:

\[ \text{Deviation} = \sqrt{\sum_{j=0}^{255} g(j) \cdot p(j)}, \]  

represents the dispersion degree of gray values;

\[ \text{Entropy} = -\sum_{j=0}^{255} p(j) \cdot \log_2(p(j)), \]  

represents the degree of uniformity of gray values in the given image: the larger the entropy, the better the uniformity will be.

Comparing with the first-order gray value features, the two-order gray value features focus more on the spatial distribution features of gray values. Based on the definition of the Gray Level Co-occurrence Matrix (GLCM), let the number of gray levels be \( L \), the size of GLCM be \( L^*L \), and \( p(k_1, k_2) \) denote the value which is positioned in the row \( k_1 \) and column \( k_2 \) of GLCM. Note that \( L=2^8 \) by definition.
Angular Second Moment (ASM) $= \sum_{k_1, k_2=0}^{\infty} p^2(k_1, k_2)$, represents the degree of spatial uniformity of the gray values and the texture thickness: the greater the ASM, the clearer the textures will be;

Contrast (CON) $= \sum_{k_1, k_2=0}^{\infty} (k_1 - k_2)^2 \cdot p(k_1, k_2)$, measures the intensity contrast between a pixel and its neighbor: the more the CON, the better the clarity of the image will be.

Note that in later application cases, the calculation of GLCM is done by using the mean value of all four directions.

**Single-Target Image Enhancement by Local HE Methods**

In a wheel’s serial number recognition case, the image enhancement is to locate the position of the wheel’s serial number. That is so-called single-target image enhancement. After the extraction of the wheel’s rim, the gray value range of the image is 0~255 while the gray value range of the serial number region is around 120~255. The original and global equalized images with respective gray histograms are shown in Fig.2 and Fig.3 below.

![Figure 2. Original rim image & Histogram.](image)

![Figure 3. Rim image equalized (global) & Histogram.](image)

Comparing the equalized gray histogram with the original one, the distribution of the gray values is in a better uniformity situation while the useless region is enlarged. The target region becomes more difficult to locate. Using those three local HE methods illustrated above:

1. Local HE based on OTSU: $b=95$, so $\Theta_{\text{OTSU}} = \{(x,y), 95 \leq g(x,y) \leq 255\}$;
2. Local HE based on mean gray value: $b=77$, so $\Theta_{\text{mean}} = \{(x,y), 77 \leq g(x,y) \leq 255\}$;
3. Local HE based on medium gray value: $b=128$, so $\Theta_{\text{med}} = \{(x,y), 128 \leq g(x,y) \leq 255\}$.

The output images and respective gray histograms are shown below in Fig.4.

![Figure 4. Rim image equalized (local) & Histogram.](image)
Comparing with the result of the global HE method in Fig.3, local HE methods have obvious advantages: the output images show that local HE methods do better as about emphasizing the target region and suppressing the useless region; the gray histograms show that local HE methods can make better uniformity effects on images, which means better contrast effects.

Among results in Fig.4, from the perspective of the suppression of useless region, Method③ does better than both Method① and Method②, while Method① does better than Method②. From the perspective of the uniformity of the gray histogram, Method③ is also better than both Method① and Method②, while Method① and Method② have a similar effect.

<table>
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<th>First-order gray value features</th>
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<td></td>
<td>Deviation</td>
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<tr>
<td>Global</td>
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<tr>
<td>Method①</td>
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<td>Method②</td>
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<tr>
<td>Method③</td>
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Comparing gray value features calculated in Table 1, local HE methods are more effective in detail emphasizing and image contrasting. Among three local HE methods, Method③ is distinguished as it has the largest CON and ASM values with other feature values well positioned as well. Method① also has good performance with a good processing balance between image details and the overall image: it positions the second in Entropy, ASM and CON values in descending order, and it also positions the second in Deviation values in ascending order. As Method① emphasizes details and ensures the uniformity of the whole image, in this case, it is a better choice.

**Multi-Target Image Enhancement by Local HE Methods**

In a surface inspection of the automobile radiator (AR), the image enhancement is to locate several surface defects. That is so called Multi-target image enhancement. The gray value range of the image is 0~255 and the gray value range of defects is around 240~255. The original and global equalized images with respective gray histograms are shown in Fig.5 and Fig.6 below.

![Figure 5. Original AR image & Histogram.](image)

![Figure 6. AR image equalized (global) & Histogram.](image)

Comparing the equalized gray histogram with the original one, the distribution of the gray values is in a better uniformity situation. Different from Case 1, here the target elements become easier to locate. Using those three local HE methods:

1. Local HE based on OTSU: b=B = 169, so \( \Omega' = \{(x,y) | 169 \leq g(x,y) \leq 255\} \);
2. Local HE based on mean gray value: b=B = 77, so \( \Omega'' = \{(x,y) | 77 \leq g(x,y) \leq 255\} \);
3. Local HE based on medium gray value: b=B = 128, so \( \Omega''' = \{(x,y) | 128 \leq g(x,y) \leq 255\} \).
The output images and respective gray histograms are show below in Fig.7.

![Fig.7 AR image equalized (local) & Histogram.](image)

It is obvious that local HE methods help better emphasize those defects and also better correct those reflection regions to some extent. And those gray histograms in Fig.7 are better uniformed than the gray histogram in Fig.6.

From the perspective of the correction of reflection regions, Method(2) does the best. Method(1) gets a better result comparing Method(3). Gray histograms in Fig.6 appear similar.

<table>
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<td>Method(3)</td>
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Comparing gray value features calculated in Table 2, as in Case 1, local HE methods are more effective in detail emphasizing and image contrasting. In this case, Method(2) shows performs the best with the largest CON and ASM values. However, the entropy value of Method(2) is the smallest. Considering its output image and the entropy value, Method(2) can cause an excessive contrast and “make” too much defects. Method(1) keeps a similar performance as in Case 1 with the second largest CON and ASM values and other well positioned feature values. Considering its balance in image details and overall image, Method(1) is a good choice in this case.

**Conclusions**

This paper analyzes and compares three local histogram equalization (HE) methods in two different cases: the image enhancement to locate wheel’s serial number, which represents a single-target image enhancement situation; the image enhancement to locate surface defects on the automobile radiator, which represents a multi-target image enhancement situation. By comparing the output images, their gray histograms and respective gray feature values, the local HE method based on OTSU is confirmed to be a good choice for the low contrast and small target image enhancement with two reasons: firstly, it shows a good balance property in emphasizing image details and equalizing the overall image; secondly, it performs more adaptive in different cases.
Acknowledgement
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References