A multi scale guided filter for illumination estimation in retinex algorithm

L Guo1, D An2,3, Y Xu3, H Li1 and M Shao3*

1 School of Mechanical Engineering, Shenyang Jianzhu University, Shenyang 110168, China
2 Research Centre for Analysis and Detection Technology, Shenyang Jianzhu University, Shenyang 110168, China
3 Research Institute for Micronano Detection and Motion Control, Shenyang Jianzhu University, Shenyang 110168, China

* E-mail: mshao@sjzu.edu.cn

Abstract. The method of illumination estimation for images affects the effect of retinex algorithm and causes information loss and halo artefact. A multi scale guided filter is proposed to estimate the illumination. In this method, bidimensional empirical mode decomposition is combined with guided filter. Firstly, the image is decomposed into multiple bidimensional intrinsic mode functions and a trend function by bidimensional empirical mode decomposition. Secondly, we use guided filter to estimate illumination information of each bidimensional intrinsic mode functions. Then illuminance component is formed by combining the illuminance information and the trend function. Finally, guided filter is again used to achieve a more accurate illuminance component. The simulation results show that multi scale guided filter can estimate the illumination component deeply and ensure the integrity of the reflection component. In the effect image of retinex algorithm, the contrast is raised by 1, the luminance is raised by 1, the information entropy is raised by 0.18, the clarity is raised by 0.001, and the visual effect is improved as a whole.

1. Introduction
Retinex theory [1] understands the luminance of human perception of objects as the organic combination of the environment illumination and the reflection of the object surface, which is composed of the illumination component and the reflection component. The illumination component depends on the source of illumination and determines the dynamic range of the image pixels. The reflection component depends on the characteristics of the object and reacts the essential characteristics of the object. Retinex theory eliminates the influence of the illumination component from the original image, obtains the reflected component, processes the reflected component and achieves the better image which is not affected by the illumination.

In recent years, the methods of illumination estimation for images based on retinex theory have appeared in many kinds of variant forms. The estimated illumination methods used are different, such as Gauss filter [2, 3], guided filter [4], bilateral filter [5, 6], BEMD [7] and wavelet [8]. However, the adaptive ability of these methods is poor and there is information loss and halo artifact.
MSGF (multi scale guided filter) is proposed for shortcomings of the above methods. This method inherits the characteristics of BEMD (bidimensional empirical mode decomposition) and guided filter and takes into account the image information and adaptability. After BEMD, the guided filter, which can estimate the illumination component of the image in depth, is used to estimate each BIMF (bidimensional intrinsic mode functions). In order to accurately estimate the illumination component, the guided filter is again used to remove the residual details after reconstructing the illumination component. MSGF is applied to retinex algorithm to carry out simulation, which is compared with the enhancement results of Gauss filter, guided filter, bilateral filter and BEMD. MSGF effectively improves the brightness and contrast of the image, improves the information loss, avoids the halo artifact and has a strong visual sense.

2. Guided filter and bidimensional empirical mode decomposition

2.1. Guided filter

The guided filter [9, 10] is a novel filter with smoothing edge, which can effectively smooth the details of the image and keep the edge features of the image scene, and does not produce the gradient reversal effect. Its principle is to filter the input image \( T \) based on the guided image \( f \). The output image \( Q \) does not only preserve the overall feature of the input image, but it can also fully obtain the change details of the guided image. Thus the guided filter can be represented as a local linear model:

\[
q_m = a_k f_m + b_k, \forall m \in w_k
\]  

In the formula: \( w_k \) is the filter window, \( m \) is the center of the filter window \( w_k \), \( q_m \) is the output of linear transformation at \( m \), \( f_m \) is the value of \( m \), \( a_k \) and \( b_k \) are the linear factors and the fixed values in the window \( m \).

\( a_k \) and \( b_k \) are solved in the following ways:

\[
a_k = \frac{1}{N} \sum_{m \in w_k} f_m t_m - \mu_k \bar{t}_k \quad \sigma_k^2 + \epsilon \quad (2)
\]

\[
b_k = \bar{t}_k - a_k \mu_k \quad (3)
\]

In the formula: \( N \) is the total number of pixels in the window \( w_k \), \( t_m \) is the value of \( m \), \( \sigma_k^2 \) and \( \mu_k \) are the variance and the mean of \( w_k \), \( \bar{t}_k \) is the mean of the filter window \( w_k \), \( \epsilon \) is the smoothing factor.

2.2. Bidimensional empirical mode decomposition

BEMD [11], which is based on the nonlinear and non-stationary data analysis, which is a multi-scale structure and which it extends the empirical mode decomposition (EMD) from one dimension to two dimensional, is a method. BEMD relies on the properties of images to decompose the image into finite BIMF and a trend function in time domain. BIMF should satisfy two constraints: (1) The local mean of the original two-dimensional signal is symmetric and its mean is 0; (2) The maximum points of the BIMF are positive and the minimum points of the BIMF are negative.

After \( J \) layers of BEMD, the final decomposition process can be expressed in the following ways:

\[
S(i, j) = \sum_{j=1}^{J} D_j(i, j) + K_j(i, j) \quad (4)
\]
In the formula: $S(i,j)$ is the original image; $D_j(i,j)$ is the $j$th BIMF; $K_j(i,j)$ is the trend function after $J$ layers of BEMD.

3. Multi scale guided filter for illumination estimation

3.1. Basic principles

The illumination components influencing the retinex algorithm can only be obtained from the original image. It is the core of the method of illumination estimation to get the illumination information. According to the core, MSGF is designed and applied to the retinex algorithm.

When BEMD is used to decompose images, the scale is automatically selected according to the characteristics of images and the details are mostly extracted. After decomposing the image by BEMD, BIMF and the trend function contain different frequency characteristics of the image. BIMF mainly contains the high frequency part of the images, which embodies some details of the images and the residual illumination information is retained. The trend function mainly contains the basic illumination information of the image. Therefore, it can result in the absence of illumination information and halo artifacts to use the trend function as the illumination component. For example, figure 2 (a) is a light image estimated by a trend function and figure 3 (a) is an image after retinex algorithm. In addition, it can effectively remove the influence of detail and illumination in the image to use guided filter estimating the illumination component. But the dynamic range of the image pixels is small, which leads to the poor visual effect of the object and cannot fully express the information of the original image. For example, figure 2 (b) is a light image estimated by guided filter and figure 3 (b) is an image after retinex algorithm.

MSGF combines with BEMD and uses guided filter to filter out the details of each BIMF and to extract illumination information. Then illuminance component is constituted by the illuminance information and the trend function. Most details of the illumination component are filtered out, but small details can be retained. Therefore, the guided filter is again used to remove the details of the illumination component. MSGF, which inherits the advantages of the guided filter, keep the edge of the images and smooth the details. And MSGF combined with BEMD to smooth the details and to remove the noise of different scales. It can effectively estimate the illumination component and reflect the illumination component. In retinex algorithm, MSGF will not cause the error of the illumination component and will not result in loss of information and halo artifact. For example, figure 2 (c) is a light image estimated by MSGF, and figure 3 (c) is an image after retinex algorithm.

![Figure 1. Original image.](image)

![Figure 2. Illumination estimation images: (a) Trend function image; (b) Guided filter; (c) MSGF.](image)
3.2. Multi scale guided filter

According to the above principles, MSGF firstly deals images with BEMD, and gets the different components of the original images. The concrete steps are as follows:

1. The trend image $K(i,j)$ is equal to the original image $S(i,j)$.
2. If $K(i,j)$ is monotonous or reaches the number of decomposition layers, the algorithm stops. Otherwise, it will make $N(i,j) = K(i,j)$.
3. Solve the extreme point of $N(i,j)$, find the regional maximum point set and the regional minimum point set and obtain the upper envelopes and the lower envelopes of the image according to the regional maximum point set and the regional minimum point set. Then calculate the envelope mean $M(i,j)$ of the image $N(i,j)$ according to the upper envelopes and lower envelopes.
4. Order $N(i,j) = N(i,j) - M(i,j)$. If $N(i,j)$ satisfies the constraint condition, the algorithm goes on. Otherwise, go to step (3).
5. Order BIMF $D(i,j) = N(i,j)$. Let $K(i,j) = K(i,j) - D(i,j)$ and go to step (2).

Secondly, each BIMF is filtered by guide filter and the illumination information is extracted. In MSGF, guided image is input image, then the formula in (2) is written as follows:

$$a_k = \frac{\sigma_k^2}{\sigma_\varepsilon^2 + \varepsilon}$$  (5)

$$b_k = \mu(1-\sigma_k)$$  (6)

Smooth BIMF $D_j(i,j)$ by formula (1) and extract illumination information $Q_{D_j}(i,j)$. It can be expressed as:

$$Q_{D_j}(i,j) = a_k D_j(i,j) + b_k$$  (7)

Then, the illuminance component is obtained by combining the illumination information $Q_{D_j}(i,j)$ and the trend function. It can be expressed as:

$$Z(i,j) = \sum_{j=1}^{J} Q_{D_j}(i,j) + K_j(i,j)$$  (8)

In the formula: $Z(i,j)$ is the illuminance component, $K_j(i,j)$ is the trend function filtered by guided filter.

Finally, guided filter is applied to the illuminance component, the details of the image are removed completely and the final illumination component $Q_X(i,j)$ is obtained.

$$Q_X(i,j) = a_k Z(i,j) + b_k$$  (9)
3.3. The application of MSGF in retinex algorithm

Through the images (f) of the following 5 sets, it is easy to find that MSGF inherits the advantages of guided filter and has a larger dynamic range of image pixels. MSGF improves the image contrast effectively, the brightness of the image and the dim image in the distance. MSGF highlights the details that are not easy to find in the image, has no halo artifact, has a strong visual sense and is more in line with the visual requirements of the human being.

4. Comparison of simulation experiments

In order to verify the effectiveness of MSGF, the simulation experiments of multiple images, which uses Gauss filter, bilateral filter, guide filter, BEMD and MSGF, are carried out on the computer, whose operating system is Windows10, whose main frequency of the processor is 2.6Hz, whose memory is 4GB, and whose software platform is Matlab2017. The result images are objectively evaluated by contrast, brightness, information entropy and clarity. The experimental images are 333×500, 390×597, 259×400, 234×350 and 234×350. The parameters of each method are set as follows: the standard deviation of Gauss filter is 250, the window of guided filter is 120×120 and BEMD decompose images 3 times which decompose images into 3 BIMF and a trend function. The results of the experiment are shown in figure 4~8.

![Image](a) ![Image](b) ![Image](c) ![Image](d) ![Image](e) ![Image](f)

**Figure 4.** First group: (a) Original image; (b) Gauss filter; (c) Guided filter; (d) Bilateral filter; (e) BEMD; (f) MSGF.

Contrast can well show the gradation level of images, and it can be expressed as:

\[ c = \sum \delta(i, j)^2 P(i, j) \]  

(10)

In the formula: \( \delta(i, j) \) is the gray difference between two adjacent pixels, \( P(i, j) \) is the probability of the gray difference \( \delta(i, j) \).
Figure 5. Second groups: (a) Original image; (b) Gauss filter; (c) Guided filter; (d) Bilateral filter; (e) BEMD; (f) MSGF.

Brightness shows the degree of light and shade of images, and it can be expressed as:

$$ a = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} g(i, j)}{mn} $$

(11)

In the formula: $g(i, j)$ is the pixel value at $(i, j)$.

Figure 6. Third groups: (a) Original image; (b) Gauss filter; (c) Guided filter; (d) Bilateral filter; (e) BEMD; (f) MSGF.
Information entropy represents the amount of information in an image, and it can be expressed as:

$$ H(p) = - \sum_{i=0}^{255} p_i \log_2 p_i $$  \hspace{1cm} (12) $$

In the formula: \( p_i \) is the probability of the \( i \)th gray level.

Clarity based on the Tenegrad gradient function shows the clarity of an image. It is defined as follows:
\[ F_{\text{Tenograd}} = \sum \sum |G(i, j)| \]  

(13)

\[ G(i, j) > \text{Tenograd} \]  

(14)

In the formula: \( \text{Tenograd} \) is 100, a given threshold of edge detection, \( G(i, j) \) is the gradient of the image.

The results of various algorithms for figure 1–5 are shown in table 1–5.

**Table 1.** First group.

|      | original image | gauss filter | guided filter | bilateral filter | BEMD     | MSGF     |
|------|----------------|--------------|--------------|------------------|----------|----------|
| contrast   | 1.5481        | 7.2407       | 12.8425      | 21.3066          | 13.0440  | 12.0827  |
| brightness | 31.4558       | 44.5080      | 19.7783      | 56.1421          | 50.7910  | 49.3690  |
| informatio n entropy | 6.637         | 7.8541       | 5.9039       | 7.5596           | 7.7483   | 7.7552   |
| clarity    | 0.0001        | 0.0007       | 0.0019       | 0.0024           | 0.0015   | 0.0014   |

**Table 2.** Second group.

|      | original image | gauss filter | guided filter | bilateral filter | BEMD     | MSGF     |
|------|----------------|--------------|--------------|------------------|----------|----------|
| contrast   | 39.1247        | 41.7655      | 62.8485      | 70.6183          | 62.7155  | 64.9710  |
| brightness | 51.5991        | 52.1697      | 58.4903      | 61.0883          | 51.2596  | 54.1183  |
| informatio n entropy | 7.4619        | 7.5958       | 6.0702       | 7.1444           | 7.2775   | 7.1907   |
| clarity    | 0.0166         | 0.0177       | 0.0213       | 0.0267           | 0.0237   | 0.0248   |

**Table 3.** Third group.

|      | original image | gauss filter | guided filter | bilateral filter | BEMD     | MSGF     |
|------|----------------|--------------|--------------|------------------|----------|----------|
| contrast   | 54.8093        | 62.5503      | 75.4751      | 105.6953         | 75.2847  | 77.1326  |
| brightness | 18.7076        | 19.9591      | 36.5361      | 30.3010          | 21.8721  | 22.1615  |
| informatio n entropy | 6.9793        | 7.0996       | 6.7446       | 7.4586           | 7.1145   | 7.1374   |
| clarity    | 0.0236         | 0.0252       | 0.0305       | 0.0400           | 0.0294   | 0.0295   |

**Table 4.** Fourth groups.

|      | original image | gauss filter | guided filter | bilateral filter | BEMD     | MSGF     |
|------|----------------|--------------|--------------|------------------|----------|----------|
| contrast   | 108.0476       | 118.2765     | 125.4374     | 156.5162         | 125.2910 | 112.3449 |
| brightness | 25.1383        | 25.4730      | 49.8711      | 36.7847          | 25.8264  | 25.7252  |
| informatio n entropy | 7.2050        | 7.2892       | 6.7322       | 7.4136           | 7.0578   | 7.1560   |
| clarity    | 0.0164         | 0.0170       | 0.0299       | 0.0264           | 0.0188   | 0.0186   |
Table 5. Fifth group.

|                      | original image | gauss filter | guided filter | bilateral filter | BEMD         | MSGF         |
|----------------------|----------------|--------------|--------------|------------------|--------------|--------------|
| contrast             | 247.5912       | 243.2520     | 106.4342     | 275.2384         | 212.1725     | 216.2456     |
| brightness           | 32.7923        | 31.1643      | 38.4612      | 40.7278          | 28.4515      | 30.7165      |
| information entropy  | 7.5167         | 7.4956       | 6.1890       | 7.6299           | 7.3181       | 7.4006       |
| clarity              | 0.0544         | 0.0537       | 0.0304       | 0.0672           | 0.0489       | 0.0508       |

The details of the result images of guided filter are more prominent. Especially in the dark, a lot of details become clearly and contrast is improved. But the edge effect of the weaker gradient is poor. The brightness and contrast of the result images of bilateral filter are improved, but the noise in the original image is amplified and the brightness of the image is saturated. The partial residual illumination of the images is not removed in BEMD, resulting in halo artifact and color distortion. MSGF has clear details, good contrast, no halo artifact, obvious characteristics and a strong visual sense.

Compared with the other four methods from table 1~5, MSGF has a great advantage in contrast, brightness, information entropy and Clarity. The overall analysis shows that the objective evaluation of MSGF is higher than other methods. For contrast, although the value of the bilateral filter high, it has a poor edge effect of the weak gradient. Therefore, MSGF has advantage in contrast. For brightness, although the value of guided filter and bilateral filter are high, the mode of luminance enhancement of guided filter is not fixed and the brightness of the image may be reduced. While the brightness of bilateral filter is too brighter, which amplify the noise in the result images and cause the brightness of the result images is supersaturated. Aiming at information entropy, the guided filter is better, but its visual effect is poor. Aiming at clarity, the guided filter has high value, but its visual effect is also poor. For every test result, MSGF is stable and not the worst. Therefore, in contrast, brightness, information entropy and definition index, MSGF has a strong advantage on the whole and the effect of illumination estimation and evaluation index are better than other methods.

In the same parameter setting, MSGF not only inherits the advantages of guided filter, but also improves the disadvantage of the image in the distance and highlights the details that are not easy to find in the image. The whole image becomes clear and the details are gradually rich. The contrast and brightness of the effect image are relatively improved, and the detail and clarity of the image become prominent. It is more consistent with human vision requirements.

5. Conclusion

According to the characteristics of retinex theory, MSGF is proposed. BIMF of different scales is obtained by using BEMD. In the process of reconstruction, guided filter is used to filter each BIMF, most of the details in the image are smoothed and the integrity of the edge is maintained. In order to filter out all details, guided filter is again used to filter the reconstruction image. Finally, MSGF is applied to retinex algorithm and the quality of the result images is evaluated by contrast, brightness, information entropy and clarity. The simulation results show that MSGF improves the contrast of the result images of retinex algorithm by 1, brightness increases by 1, information entropy increases by 0.18 and the definition increases by 0.001. MSGF avoids halo artifact and information loss, highlights fine segments of the image and meets the visual vision of the human senses. Therefore, MSGF can estimate image illumination information effectively.

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