An Improved Adaptive Fusion Image Windows Based Technology

Hui Xia

***Abstract*—In dim condition, by using a light sensor and infrared sensor can make up for human's visual defects and make better observation of the object and background environment. If combining the image information from the two sensors at the same time and the same place, you can generate a new image with more information, precision and credibility; however traditional windows based weighted average fusion algorithm has some limitations, the paper put forward an fusion algorithm with an improved adaptive threshold based on windows in dim conditions. By contrast experiment, it proved that the value of entropy, average gradient and edge retention of the improved method have been all increased, and the effect of image fusion has also been changed better.**

***Index Terms*—Algorithm, fusion image, entropy, edge preserving degree.**

I. Introduction

Image fusion technology is collecting image data from a variety of image information on the same target after the image processing and computing technology, to maximize the extraction of useful information from each channel, and finally integrated into high-quality images to improve image information utilization and the computer interpretation accuracy and reliability. Algorithm will often combine with soma evaluation information values such as image fusion, average entropy value, standard deviation, and average gradient, which reflect the tiny details in the image contrast and texture variation, and also reflect the sharpness of the image.

This paper uses two kinds of image (dim and infrared image) after Laplacian pyramid decomposition [1], and then processes fusion operation [2] according to some fusion rules of decomposed coefficients. And fusion rules are the essence of the whole process of image fusion, we are here to study fusion rules improvement.

Traditional windows-based coefficient weighted average fusion algorithm[3] is taking into account the fused image correlation between adjacent coefficients, namely, fusion rules of high frequency coefficient adopt the weighted average fusion rules.

However, improved adaptive algorithm use the proportion of average energy [4] to express the high-frequency part of the final improved weight coefficient of the fusion image.

By such a way, it is more accurate than by using traditional algorithm to refer to coefficient's maximum or minimum value.

And experimental data show that image information entropy, average gradient and edge retention value have all been improved by using the improved image fusion weight coefficient algorithm.

II. The Traditional Image Fusion Process and Algorithm

A. Transform Domain Image Fusion Process

Using image fusion algorithm based on the changing domain is to use a certain image conversion method [5] (such as wavelet transform, pyramid transform, discrete cosine transform) to make a multi-scale decomposition [6] and after that you can get a fused image coefficient for each of the image, and then under a certain fusion rules, the final fusion image coefficient is merged by each group of fusion data, and finally image fusion is formed after the image's inverse transform. Fig. 1 shows its fusion process.

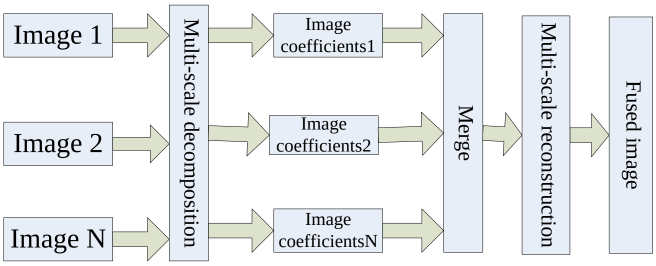

Fig. 1. Image fusion process based on transformation.

B. Traditional Adaptive Fusion Algorithm

$f^A(x,y)$ and $f^B(x,y)$, respectively, denotes subband coefficients of infrared image and LLL(low light level) image after decomposition in low frequency, $h_i^A(x,y)$ and $h_i^B(x,y)$, respectively represents coefficient of infrared image and LLL image $(i = 0,1\cdots,N-1)$ in high-frequency subband, Wherein N represents the layers of the image decomposition; $f^F(x,y)$ represents the fusion coefficient of the low subband, and $h_i^F(x,y)$ represents the various fusion coefficient of high-frequency sub-band $(i = 0,1\cdots,N)$.

Eq. (1) shows the low-frequency part of the image integration rules, which use the average coefficient of the

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infrared images A and LLL image B.

$$f^F(x,y) = \left(f^A(x,y) + f^B(x,y)\right)/2 \quad (1)$$

However, the high frequency portions of the image integration rules are as following:

First, (we may set a square window for example) calculate the importance of coefficient of the small selected windows T, moving the center of the windows to the position of the current fusion coefficient, obtaining weighted average energy value of the windows area as a measure to evaluate the importance of the coefficient. Eq. (2) shows the relation of the average energy and the weight coefficient as below.

$$S_i^I(x,y) = \sum_{l\in(-L,L)} k(l)\left[h_i(x+l,y+l)\right]^2 \quad I = A,B \quad (2)$$

where in $k(l)$ represents weight coefficient, and satisfies the equation $\sum_{l\in[-L,L]} k(l) = 1$, also side length of the windows equals ($2L+1$), $S_i^I(x,y)$ denotes the weighted average energy.

And then calculate the normalized similarity of the coefficients of the infrared image A and LLL image B in corresponding windows areas. $S_i^A(x,y)$ and $S_i^B(x,y)$ respectively, denotes average energy of infrared image and LLL (low light level) image. So the fusion similarity degree $M^i_{AB}(x,y)$ can be denoted as below Eq. (3):

$$M^i_{AB}(x,y) = \frac{2\sum_{l\in(-L,L)} k(l)\; h_i^A(x+l,y+l)\; h_i^B(x+l,y+l)}{S_i^A(x,y) + S_i^B(x,y)} \quad (3)$$

Finally, Setting a similarity threshold α ,if $M^i_{AB}(x,y) < \alpha$,then the Fusion coefficient of the i-th high frequency subband $h_i^F(x,y)$ is as below Eq. (4).

$$h_i^F(x,y) = \begin{cases} h_i^A(x,y) & if\ \ S_i^A(x,y) \ge S_i^B(x,y) \\ h_i^B(x,y) & if\ \ S_i^A(x,y) < S_i^B(x,y) \end{cases} \quad (4)$$

Namely, take coefficient of the corresponding frequency band with the higher importance from the source image as the coefficient of the fused image band.

Similarly, if $M^i_{AB}(x,y) > \alpha$, then fusion coefficient $g_i^F(x,y)$ of the i-th high frequency subband coefficient is:

$$g_i^F(x,y) = \omega_A h_i^A(x,y) + \omega_B h_i^B(x,y) \quad (5)$$

Namely, taking the weighted average of the corresponding coefficients of image A and image B, corresponding weighted coefficient value of ω_A, ω_B is as below Eq. (6)-(9).

$$\omega_A = \begin{cases} \omega_{\min} & if\ S_i^A(x,y) \ge S_i^B(x,y) \\ \omega_{\max} & if\ S_i^A(x,y) \le S_i^B(x,y) \end{cases} \quad (6)$$

$$\omega_B = 1 - \omega_A \quad (7)$$

So we can get the following equations as below:

$$\omega_{\min} = 1/2 - 1/2\left(1 - M^i_{AB}(x,y)\right)/\left(1-a\right) \quad (8)$$

$$\omega_{\max} = 1 - \omega_{\min} \quad (9)$$

III. Objective Assessment Method and Algorithm

Objective evaluation methods [7] of image fusion can be roughly divided into two categories: independent single factor rating and a joint single factor evaluation. Factor of independent factors rating include: information entropy, average gradient and edge retention [8]-[11].The paper mainly make a study of independent factors rating.

A. Information Entropy

The image information entropy indicates how much amount of information is contained in the image, the greater the information entropy is, the more image information it contains. The fused image contains even more information than that in the source image; the greater of the fusion image information entropy indicates that the effective of fusion is better. The image information entropy E is defined as below equation (10):

$$\mathrm{E} = -\sum_{i=0}^{L-1} P(i)\log_2 P(i) \quad (10)$$

where in $P(i)$ denotes the proportion of gray values in the image, L means the gray level of the image.

B. Average Gradient

Evaluation of image clarity, which is defined as below Eq. (11):

$$\nabla \bar{G} = \frac{1}{M\times N}\sum_{m=1}^{M}\sum_{m=1}^{N}\sqrt{\Delta F_x^2(m,n) + \Delta F_y^2(m,n)} \quad (11)$$

$\Delta F_x(m,n)$ and $\Delta F_y(m,n)$ respectively represents the difference of the fused image function $F(m,n)$ in the x-direction and y-direction. The average gradient is not only able to evaluate the clarity of the image, but also to evaluate the degree of image details contrast and texture variation. In general, the larger the average gradient value is, the higher the sharpness of the image will be, and the better of the fusion is.

C. Edge Retention

Edge retention denotes fused image on the holding degree of the edge of the source image information, which is an important measure of image fusion indicators.

Source image A, image B, and the fused image F, for example, to maintain a degree of image edge information $Q_p^{AB/F}$ is defined as following equation:

$$Q_p^{AB/F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} Q_{AF}(n,m)\omega_A(n,m) + Q_{BF}(n,m)\omega_B(n,m)}{\sum_{n=1}^{N}\sum_{m=1}^{M}(\omega_A(n,m)+\omega_B(n,m))} \quad (12)$$

where in,

$$Q_{AF}(m,\ n) = Q_{AF}^{g}(m,n)Q_{AF}^{a}(m,n),$$

$$\omega_A(n,m) = |g_A(n,m)|^L,\quad \omega_B(n,m) = |g_B(n,m)|^L,$$

$Q_{AF}^{g}(m,n)$, $Q_{AF}^{a}(m,n)$ denote the degree of maintaining information, and $g_A(n,m) = \sqrt{S_A^x(n,m)^2 + S_A^y(n,m)^2}$, $S_A^x(n,m), S_A^y(n,m)$ respectively says the obtained result from image A horizontal filter and vertical filter by Sobel operator,L is constant, range for edge retention is: $0 \le Q_p^{AB/F} \le 1$.

In the same way, we can get $Q_{BF}(n,m)$ and $\omega_B(n,m)$.

D. Design and Realization of Fusion Evaluation Module

```
for i = 1 → M
    for j = 1 → N
        if (gB(i, j) > gF(i, j))
            GBF(i, j) ← gF(i, j) / gB(i, j);
        else
            if (gB(i, j) == gF(i, j))  GBF(i, j) ← gF(i, j);
            else
                GBF(i, j) ← gB(i, j) / gF(i, j);
            end
        end
        ABF(i, j) ← 1-abs(aB(i, j)-aF(i, j)) / (pi/2);
        QgBF(i, j) ← Tg / (1 + exp(kg * (GBF(i, j) − Dg)));
        QaBF(i, j) ← Ta / (1 + exp(ka * (ABF(i, j) − Da)));
        QBF(i, j) ← QgBF(i, j)*QaBF(i, j);
    end
end
//calculate edge retention;
    d ← sum(sum(gA + gB));
    n ← sum(sum(QAF.*gA + QBF.*gB));
    QABF ← n/ d;
```

Fig. 2. Computing image edge information preservation.

Step 1: Design goals: Assess image fusion effects objectively;

Step2: Module function: Calculate the fused image information entropy, edge retention and average gradient;

Step3: Core algorithm: Fusion evaluation module in the core part of the algorithm is as follows Fig. 2, which shows the core part algorithm of computing image edge information preservation; Fig. 3 shows the core part algorithm of computing image entropy [12].

```
for i=1 → m
        for j=1 → n
            k ← (i, j) + 1;
            num(k) ← num(k) + 1;
        end
    end
    P(i) ← num(i)
for  i=1 → M;
    Entrophy ← Entrophy  -P(i) * log2 P(i);
end
```

Fig. 3. Computing image entropy algorithm.

IV. Improved Adaptive Threshold Fusion Algorithm

Above traditional windows adaptive image fusion algorithm, which is based on the image coefficients weighted average fusion rules. We have come to the view that the high-frequency subband of the fusion coefficient depend on the similarity threshold.

If similarity threshold of different fused image is only simply set to a same fixed value, which is unreasonable. For example, if the two fused image's degree of correlation is relatively low (e.g. in the infrared and LLL image fusion, the image of the target object is often shielded by scene in the low-light, but it will not be shielded in the infrared image [13], so the two image's correlation will be relatively low), then we'd better set a smaller "α"; conversely, if the two images have high degree of correlation, then we should set a bigger "α". Therefore, this paper put forward an improved windows based adaptive threshold fusion algorithm.

Take the two grayscale and same size images A& B, and the below equation (13) can be used to measure its image correlation [14].

$$C = \left| \frac{\sum_m\sum_n\left(A_{mn} - \bar{A}\right)\left(B_{mn} - \bar{B}\right)}{\sqrt{\left(\sum_m\sum_n\left(A_{mn} - \bar{A}\right)\right)^2\left(\sum_m\sum_n\left(B_{mn} - \bar{B}\right)\right)^2}} \right| \quad (13)$$

where in A_{mn}, B_{mn} respectively represent grayscale of the images $\bar{A}$, $\bar{B}$ matrix, $\bar{A}$, $\bar{B}$ respectively represent the mean value of A_{mn}, B_{mn}. The range of C and α value is as below:

$0 \le C_1 \le C_2 \le 1, \alpha_1 \le \alpha_2 \le \alpha_3$, the greater is the value of "C", the greater the similarity of the two images.

In this experiment, we can first calculate fused image's degree of correlation in each group in the image database, and then set them into three groups by using a linear classification as following scope:

$$[0, C_1], [C_1, C_2], [C_2, 1], 0 \le C_1 \le C_2 \le 1,$$

These three intervals, respectively, are corresponding to the three fusion computing similarity threshold α_1, α_2, and α_3 in high-frequency subband, wherein $\alpha_1 \le \alpha_2 \le \alpha_3$. So the fusion arithmetic similarity threshold value of high frequency subband is as following Eq. (14).

$$a = \begin{cases} a_1 & if\ 0 \le C \le C_1 \\ a_2 & if\ C_1 < C < C_2 \\ a_3 & if\ C_2 \le C < 1 \end{cases} \tag{14}$$

In the new algorithm, fusion weight coefficient has also been modified. If $M_{AB}^{i}(x, y) > \alpha$, then the fusion processing is:

$$g_i^F(x, y) = \omega_A h_i^A(x, y) + \omega_B h_i^B(x, y) \tag{15}$$

where in $h_i^A(x, y)$ and $h_i^B(x, y)$, respectively represents the high-frequency sub-band coefficient of infrared image and LLL image.

Namely, ω_A, ω_B respectively denotes the weighted average of the corresponding coefficients of image A and image B, and corresponding weight coefficient ω_A, ω_B is showing as below equation:

$$\omega_A = s_A / (s_A + s_B), \omega_B = s_B / (s_A + s_B) \tag{16}$$

s_A, s_B respectively denotes average energy of infrared image and LLL(low light level) image; Using the proportion of windows area weighted average energy as weight coefficient is more reasonable.

V. Experimental Results and Analysis

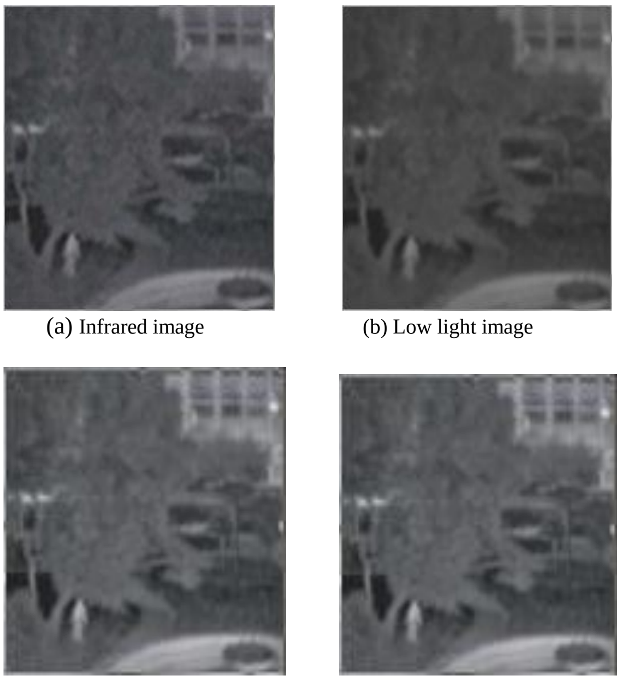
The experiments selected 4 groups of infrared and LLL image to make fusion. Using Laplacian pyramid transform as multiscale decomposition method, the high frequency part of the fusion source image respectively adopt the traditional weighted average fusion algorithm and improved algorithm based on windows adaptive thresholds. The data contrast effect is showing in Table I.

As can be seen from the table, using an improved window-based adaptive threshold, the information entropy of fusion image, the edges of the image and the average gradient all have been improved.

TABLE I: Contrast of the Traditional Windows Coefficients Weighted Algorithm and Improved Algorithm

Group Name	High-frequency Fusion Rule	Fusion Evaluation Module		
		Information Entropy	Edge Retention	Average Gradient
Group A	Windows coefficients weighted	6.4382	0.5257	3.8148
Group B		6.6003	0.5432	3.7925
Group C		6.4111	0.5069	3.7468
Group D		6.618	0.5141	3.8024
Group A	Improved Algorithm	6.4384	0.5259	3.8152
Group B		6.6005	0.5436	3.8914
Group C		6.4116	0.5072	3.8001
Group D		6.6201	0.5151	3.8143

Finally, through computer simulation software to simulate the fusion images before and after improving to make a contrast. The experiment respectively used traditional algorithms and improved fusion algorithm by using real viewfinder under the low level light and infrared light condition to get the final image contrast. It proved that improved integration of image is significantly better than the traditional one, as shown in Fig. 4.



(a) Infrared image (b) Low light image

(c) Fused image (d) Improved Algorithm Fusion Image

Fig. 4. Fusion images contract traditional algorithm and improved one.

VI. Conclusion

This paper is based on traditional classical fusion algorithm; starting with the calculation of fusion coefficient in high-frequency image to find its flaws, and using four different groups of image fusion experiments to find the differences between the existing and the improved one. Finally we get the experimental result by using both traditional and improved algorithm through some important image evaluation methods data, such as information entropy, the edges of the image and image of the average gradient.

After experiment, we get the conclusion that all the evaluation methods data have been improved, and get the more perfect quality image. The experimental data indicate that it can obviously improve the effect of image fusion through using the new adaptive algorithms.

Experimentation results show that the proposed improved method performs better than the existing one.

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