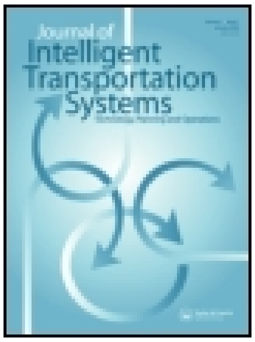

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A novel infrared image enhancement based on correlation measurement of visible image for urban traffic surveillance systems

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ABSTRACT

Infrared imaging sensors are widely employed in urban traffic systems since they are not affected by lighting conditions. However, due to the limitation of hardware and imaging environment, it is difficult to obtain infrared (IR) images at the desired quality. IR images always lack detailed information, which leads to unsatisfying IR image enhancement results with the conventional method. Compared with the IR images, the visible (VIS) images contain detailed information, which could help to enhance the quality of the corresponding IR images. In this article, we propose an effective method to enhance IR images by applying the multi-sensors image. First, we adopt the edge-preserving filter to decompose the IR and VIS images into illumination and reflectance components according to Retinex theory. Second, each region in the IR and VIS image is classified into the related region and non-related region according to the correlation between IR and VIS images. Finally, an adaptive fuzzy plateau HE (AFPHE) is utilized to enhance the illumination component, and a strategy is employed to enhance the detail of the IR reflectance component with the help of VIS images. Experimental results demonstrate that the proposed method can effectively improve the contrast and enhance the detail of the IR images.

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KEYWORDS
Urban traffic; IR image enhancement; Retinex theory; image correlation

1. Introduction

Intelligent transportation system (ITS) is an advanced application based on modern electronic information technology. It aims to provide innovative services relating to different modes of transport (Ran, Jin, Boyce, Qiu, & Cheng, 2012). Infrared imaging sensor, as one important component in ITS, detects radiation in a long-wave electromagnetic spectrum to obtain IR images (Noda et al., 2001; Wu et al., 2017). It is not affected by lighting conditions (Ming, Zheng, & Liu, 2016), thus can work stably around the clock. Infrared (IR) images facilitate the subsequent processing of intelligent transportation systems (Xu et al., 2019). However, the original IR images usually have a signal-to-noise ratio (SNR) and low contrast due to the factors, i.e., the limitations of IR sensors and unfavorable environmental conditions, which reduce the quality of IR images (Ring, 2010). The low-quality IR images may fail many applications, which include segmentation (Feng, Wenkang, Liangzhou, Yong, & Zhenfu, 2005; Shi & Malik, 2000), tracking (Tai, Tseng, Lin, & Song, 2004), surveillance (Cong, Khoudour, Achard, & Bruyelle, 2011), object recognition (Lowe, 1999). Therefore, enhancing the quality of IR images, as shown in Figure 1, is of great significance for ITS.

Generally, the quality of IR images can be enhanced from two techniques. One technique is to improve hardware of the sensors (Bastani, Kong, Huang, & Zhou, 2016), another is to exploit image processing (Joro et al., 2008), (i.e., IR image enhancement). Improving hardware of the sensors is a straightforward technique to enhance the quality of IR images. However, this technique would be very expensive and time consuming. Another low-cost technique, i.e., IR image enhancement, which is convenient to improve the quality of IR images. The existing IR image enhancement can be classified into two categories: homogeneous image enhancement, heterogeneous image enhancement. Figure 2 shows the classification of image enhancement.

Homogeneous image enhancement is to enhance the image by only exploiting the information of one single type image. Homogeneous image enhancement, which includes histogram correction, edge

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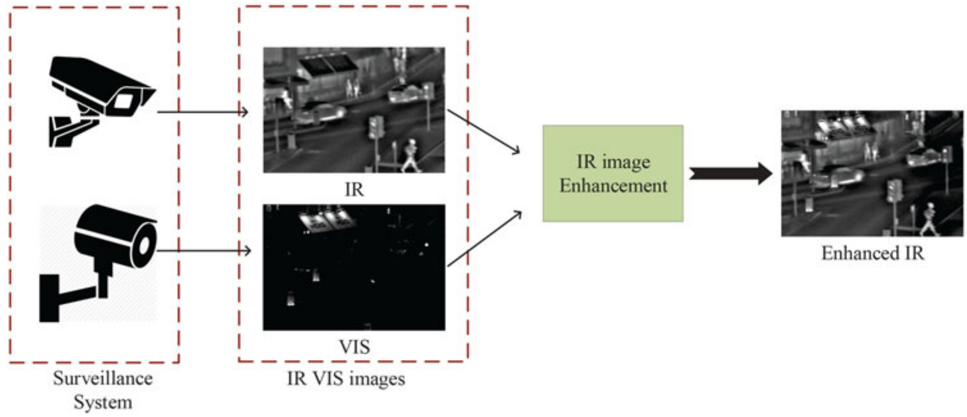

Figure 1. The applications of IR image enhancement for the surveillance system.

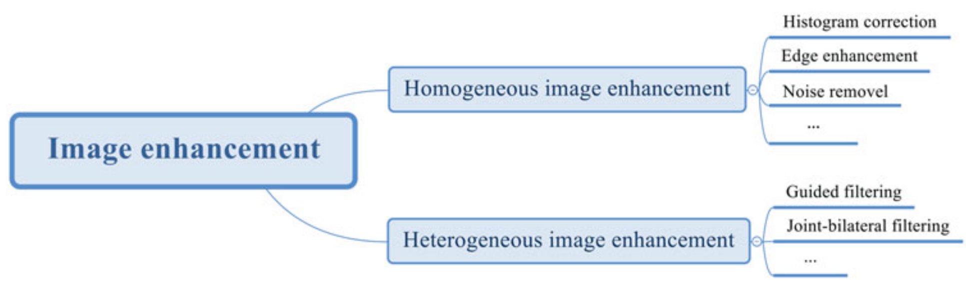

Figure 2. Classification of image enhancement.

enhancement, noise removal, and amplitude scaling (Tao et al., 2017), is a traditional image enhancement technique. This method is simple and effective for certain images, but it is not applicable to all images.

Histogram equalization (HE) is a simple and effective image enhancement method, which improves global contrast of images by redistributing probability distribution function (PDF) equally in the histogram of the enhanced image (Xia et al., 2016). Lu et al. present plateau HE (PHE) in (Lu, Tang, Zhou, Yang, & Lin, 2012), which uses a platform histogram to enhance the IR image. This method is simple and efficient, and can better enhance the contrast of the IR image. A fuzzy PHE (FPHE) is proposed in (Wu et al., 2017) for IR image to improve global contrast. The double plateaus HE (DPHE) is proposed in (Liang, Ma, Xie, Zhou, & Wang, 2012; Song, Shao, & Jun, 2008), which enhances the target and the details of the image by setting lower bound thresholds. However, this method is easy to result in the detail of images absence in the processing of equalization and cause over-enhancement for images with much detailed information (Stark, 2002).

Homomorphic filtering is an image enhancement method that combines an image gray level transformation and frequency domain. Einshoka, Kelash, Faragallah, and Elsayed (2014) use homomorphic filtering to enhance IR images. This method performs well for the images of uneven illumination. In (Guan & Wan, 2016), Guan and Wan propose an unsharp masking sharpening method to suppress noise and sharpen images. This method is strict for the size of the template. In (Ni, Li, & Xia, 2008), a method that adopts image denoising and edge enhancement for IR images enhancement. A particle swam optimization-based local entropy weighted histogram equalization for IR image enhancement is proposed in (Wan et al., 2018). A novel approach to predict the target and background features based on convolutional neural network is proposed in (Fan et al., 2018). A new algorithm to enhance the contrast of infrared image is proposed in (Wang, Chen, & Liu, 2019). Based on multiscale top-hat transform, a method is proposed in (Bai, Zhou, & Xue, 2011) for enhancing IR images through improving contrast. In (Land & Mccann, 1971), Land and Mccann propose a Retinex theory that is widely applied in image enhancement. Retinex theory is a model based on the human visual system, which is adopted to adjust the color and brightness of the perceived object. In the Retinex theory, the reflectance properties of a target can be expressed by reflectivity (Jobson, Rahman, & Woodell, 1997; Land, 1977; Rahman, Jobson, & Woodell, 2002; Rahman, Jobson, & Woodell, 2004). Therefore, we can acquire the reflectance component of an object by applying this method. However, this method usually engenders halo artifacts and low contrast. In (Tao et al., 2017), Tao et al. propose a Retinex-based framework to enhance images and to reduce these artifacts effectively. In (Elad, 2005; Kimmel, Elad, Shaked, Keshet, & Sobel, 2003), enhances image contrast through altering the proportion of the illuminance component and reflectance component of an original image in the Retinex model.

The homogeneous image enhancement only adopts one type of image to enhance the image. To overcome this problem, heterogeneous image enhancement, which enhances the image with the help of different type images, is proposed. In recent years, guiding filtering (He, Sun, & Tang, 2010), joint-bilateral filtering (Camplani, Mantecon, & Salgado, 2013), joint filtering (Shen, Zhou, Xu, & Jia, 2015) are introduced to heterogeneous image enhancement. He et al. propose a joint-bilateral filter in (Camplani et al., 2013) that improve the edge region sharpness of the depth image with the help of visible (VIS) images. Camplani et al. in (He et al., 2010) use guided filter for enhancing the detail of the edge region of depth images with VIS images. However, the method is easy to introduce artifacts. The joint filtering, is proposed in (Shen et al., 2015) by Shen et al., can effectively maintain the detail of the target image when the heterogeneity image filtering.

Due to the IR images and its corresponding VIS images have some extent of correlation, in this article, we propose a novel heterogeneous IR image enhancement method with the help of the VIS image. First, we utilize the WLS filter to acquire the illumination component precisely based on the Retinex theory. The corresponding reflectance component can be estimated by dividing the original image by its illumination component. Then, we adopt different strategies to deal with the illumination and reflectance components. We apply an adaptive fuzzy PHE for illumination component to ameliorate global contrast. A non-local means filter is adopted to weaken the noise for reflectance component. Each region in the IR image can be classified into a related region or a non-related region according to the relationship between the region in the IR image and its corresponding region in the VIS image. The related regions and the non-related regions in the reflectance component are enhanced with different strategies. Subsequently, non-local filtering is applied again for the enhanced reflectance component to suppress image noise. Finally, the result is synthesized with the processed illumination and reflectance components.

The contributions of this article as follows:

1. We decompose the IR and VIS images into illumination and reflectance components according to the Retinex theory which can reasonably estimate the noise in an image and remove it. And applying the WLS filter does not produce halo at the edge.
2. An adaptive fuzzy PHE is proposed to enhance the global contrast of the illumination component while also overcoming the trouble of noise amplification.
3. The contrast and sharpness of VIS images are generally superior to IR images. Using the correlation between the two, the VIS images can effectively enhance the contrast and detailed information of the IR images and improve its visual effect.

The rest of this article is organized as follows. Section 2 introduces the proposed method. The experimental results and analyses are shown in Section 3, and in Section 4 presents the conclusion.

2. Proposed method

The framework of the proposed method is shown in Figure 3. It involves five main phases: decomposition, correlation measurement, reflectance component enhancement, illumination component enhancement, and image reconstruction. First, according to the Retinex theory, we utilize the WLS filter to acquire the illumination component precisely. The corresponding reflectance component can be estimated by dividing the original image by its illumination. Second, we apply an adaptive fuzzy PHE (AFPHE) for illumination component to ameliorate global contrast. Third, a non-local means filter is adopted to weaken the noise for reflectance component. Then, each region in the IR image can be classified into a related region or a non-related region according to the relationship between the region in the IR image and its corresponding region in the VIS image. The related regions and the non-related regions in the reflectance component are enhanced with different strategies. In addition, the non-local filtering is applied for the enhanced reflectance component to suppress image noise. Finally, enhanced illumination and reflectance components multiplied to obtain the result.

2.1. Illumination and reflectance estimation

The basic hypothesis in Retinex theory regards an image $I(i, j)$ as the product of the illumination $L(i, j)$ and reflectance $R(i, j)$:

$$I(i,j) = L(i,j) \times R(i,j). \tag{1}$$

The committed step in Retinex theory is to estimate the illumination component. Figure 4 shows

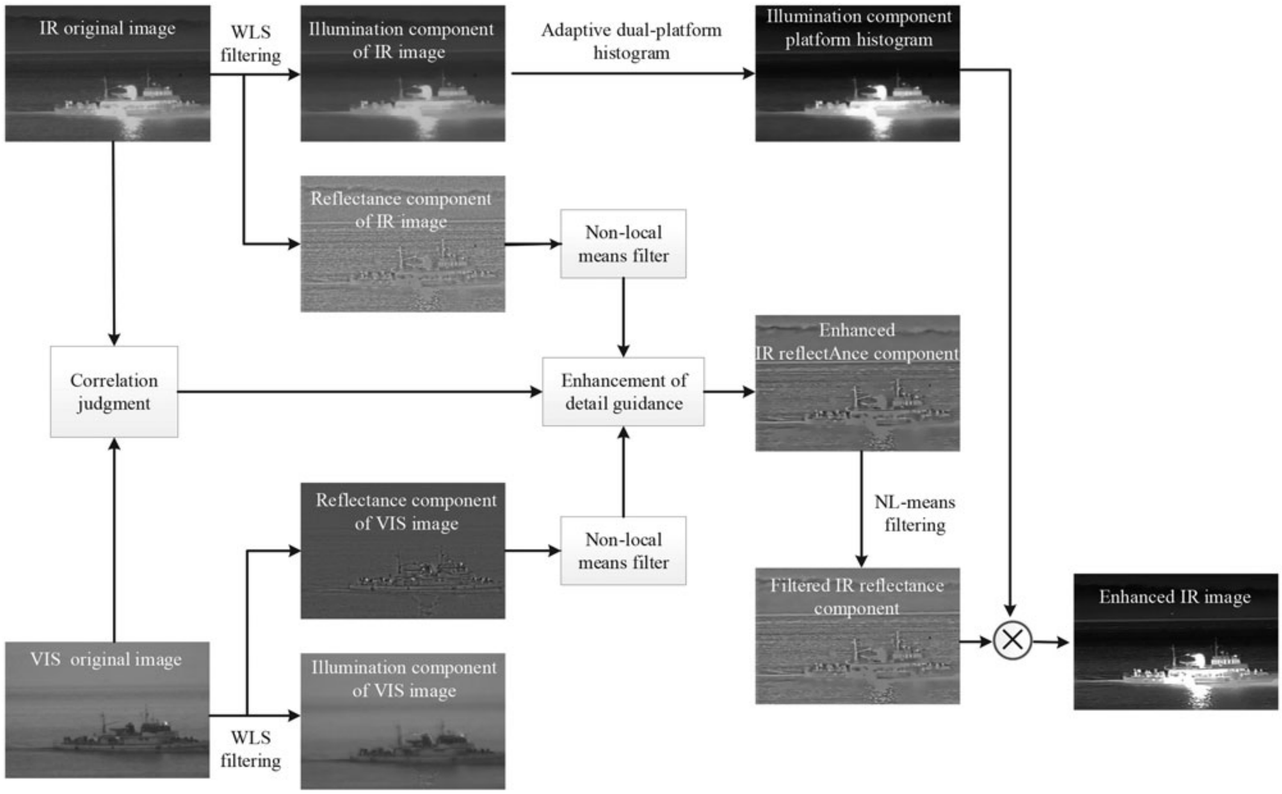

Figure 3. Flowchart of the proposed method.

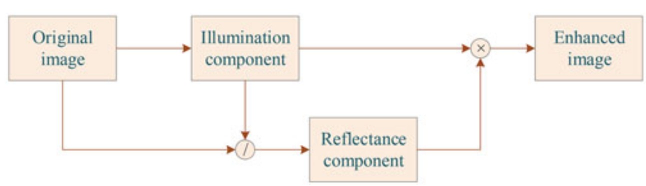

Figure 4. Flowchart of estimating illumination and reflectance components according to Retinex theory.

a flowchart of estimating illumination and reflectance components according to Retinex theory.

In view of a smooth version of the original image is usually regarded as the illumination component, we can reckon illumination by applying a low-pass filter. Herein, an edge-preserving filter, i.e., WLS filter is used to estimates the illumination component. Then, the reflectance component is derived by dividing the original image by its illumination component.

2.2. Related and a non-related region partition

As IR images and its corresponding VIS images are correlated with each other and the VIS images contain more details in comparison with its corresponding IR images, we can enhance IR images with the help of VIS images. Not all the regions in the IR image are similarly correlated with its counterpart regions in the VIS image. Those regions, which are strongly correlated with its counterpart regions, can be considered as the related regions, while those regions, which have weakly or no relationship with its counterpart regions, can be considered as the non-related regions. Figure 5 illustrate the diagram of dividing related and non-related regions.

2.2.1. Non-local self-similarity

Image self-similarity is important because it forms the basis for many imaging techniques such as non-local means denoising and fractal image coding. The feature of a patch can be represented by the relationship of its self-similarity. In an image, similar patches existed for arbitrary image patches, and its attributes can be expressed by self-similarity (Benabdelkader, Cutler, Nanda, & Davis, 2001; Deselaers & Ferrari, 2010; Shechtman & Irani, 2008). Gray information can characterize the objective nature of images, with accurate, stable and other features. In the proposed method, the

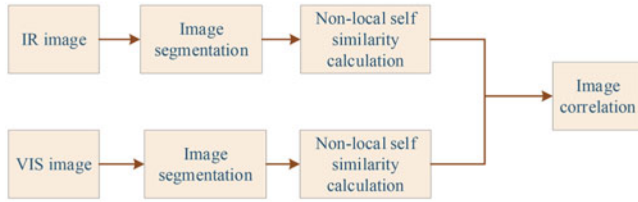

Figure 5. Diagram of dividing related and non-related regions.

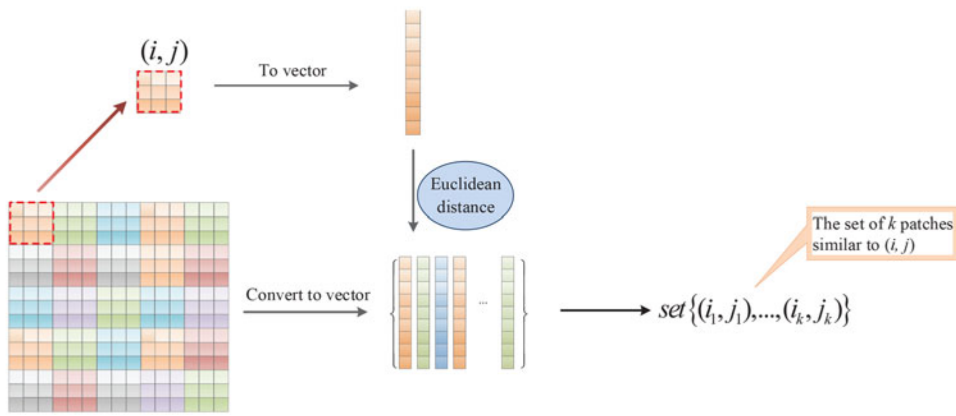

Figure 6. Schematic of self-similarity measurement.

Euclidean distance (Elmore & Richman, 2001; Li & Lu, 2009) is employed to measure the similarity of image patches. In Eq. (2), $d(i, j)$ is the distance between (i, j) and surrounding points. Figure 6 shows the schematic of self-similarity measurement.

$$d(i,j) = \sqrt{\sum_{m,n=1}^{k} \left\{ (i_m - i_n)^2 + (j_m - j_n)^2 \right\}}. \tag{2}$$

The similarity calculation of image patches with centered pixel(i, j) as follows:

Taking the pixel(i, j) as the center to acquire the target image patches and convert it into the target vector representation.

1. Obtaining a non-local searching zone centered at pixel(i, j), is shown as a dotted box $N \times N$ in Figure 6.
2. Dividing searching regions into patches by pixel and expressing in terms of vectors. Subsequently, computing the Euclidean distance between vectors and target vector.
3. The distance is sorted in ascending order to find K positions set $\{(i_1, j_1), (i_2, j_2), \ldots, (i_k, j_k)\}$ closest to the vector of image patches where the pixel(i, j).

2.2.2. Correlation measurement

We measure correlation by adopting the self-similarity of IR and its corresponding restarted VIS images.

Let the set of K similar image patches which closest to the IR patches of the pixel (i_{IR}, j_{IR}) is $\text{set}_{IR}\{(i_{IR1}, j_{IR1}), (i_{IR2}, j_{IR2}), \ldots, (i_{IRk}, j_{IRk})\}$.

And its corresponding VIS image patches of the pixel (i_{VIS}, j_{VIS}), the set of K similar image patches is $\text{set}_{VIS}\{(i_{VIS1}, j_{VIS1}), (i_{VIS2}, j_{VIS2}), \ldots, (i_{VISk}, j_{VISk})\}$.

The correlation coefficient (CS) between the IR pixel (i_{IR}, j_{IR}) and the VIS image pixel (i_{VIS}, j_{VIS}) can be expressed as:

$$CS = \begin{cases} 1 & \text{set}_{IR} = \text{set}_{VIS} \\ \dfrac{n}{k} & G(\text{set}_{IR} \cap \text{set}_{VIS}) = n \\ 0 & G(\text{set}_{IR} \cap \text{set}_{VIS}) = 0 \end{cases}, \tag{3}$$

where $\cap$ indicates intersecting operations; and $G(\cdot)$ denotes the number of common elements of two sets. In the proposed method, when $CS = 1$, the IR and VIS images at (i, j) are related regions. The flowchart of correlation measurement is expressed in Figure 7. Figure 8 shows an example of correlation, where white is the related regions and black is the non-related regions.

2.3. Reflectance component enhancement

2.3.1. Enhancement based on correlation measurement

When the quality of VIS images is better than IR images, the extracted detail and contour clarity of the reflectance component from VIS images is often

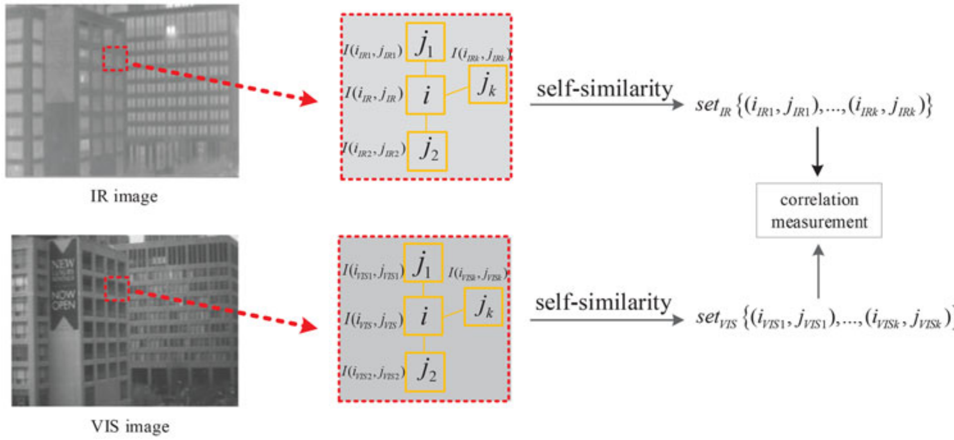

Figure 7. Flowchart of correlation measurement.

(a) IR image (b) VIS image (c) Correlation image

Figure 8. An example of correlation. (a) IR image; (b) VIS image; (c) Correlation image.

higher than the IR images. Utilizing the correlation between IR and VIS images with detail clarity can effectively enhance the detail of IR images.

At the related regions of IR and VIS images, we enhance the detail of the IR reflectance component with VIS reflectance component guided. While in its non-related region, the IR reflectance component $R_{IR}(i_I, j_I)$ keep constant. The enhanced IR reflectance component $R_{IRC}(i_I, j_I)$ can be expressed as:

$$\begin{cases} R_{IRC}(i_I, j_I) = C_1 R(i_I, j_I) + C_2 R(i_V, j_V) & \text{relatedregions} \\ R_{IRC}(i_I, j_I) = R(i_I, j_I) & \text{non-relatedregions} \end{cases}, \tag{4}$$

where $C_1 + C_2 = 1$. According to the experimental tests, we take $C_1 = 0.3, C_2 = 0.7$. Figure 9 shows the process of enhancement with detail guided.

2.3.2. Image de-noising

To further improve the IR reflectance component, we exploit non-local means filter(Buades, Coll, & Morel, 2005; Salmon, 2010; W. G. Zhang & Zhang, 2011; Zhong, Yang, & Zhang, 2012) to suppress image noise. The formula can be regulated as:

$$NLv(i) = \sum_{i \in \Omega} w(i, j) u(i), \tag{5}$$

where $u(i)$ and $NLv(i)$ indicates the pixels in the reflectance component and its corresponding filtered component at position i. Ω represents the image domain. $w(i, j)$ denotes the weight of pixel i relative to j of original reflectance component. $0 < w(i, j) < 1, \sum_j w(i, j) = 1$.

2.4. Illuminance component enhancement

We apply an AFPHE for illuminance component to ameliorate global contrast. The PDF can be given by

$$P_T(l) = \begin{cases} \frac{n_l}{N} & P(l) < T \quad 0 \le l \le 255 \\ T & P(l) \ge T \quad 0 \le l \le 255 \end{cases}, \tag{6}$$

where $l = 0, 1, 2, \ldots, 255$. n_l is the number of pixels with lth gray level. N denotes the total number of pixels in the image. T is a plateau threshold.

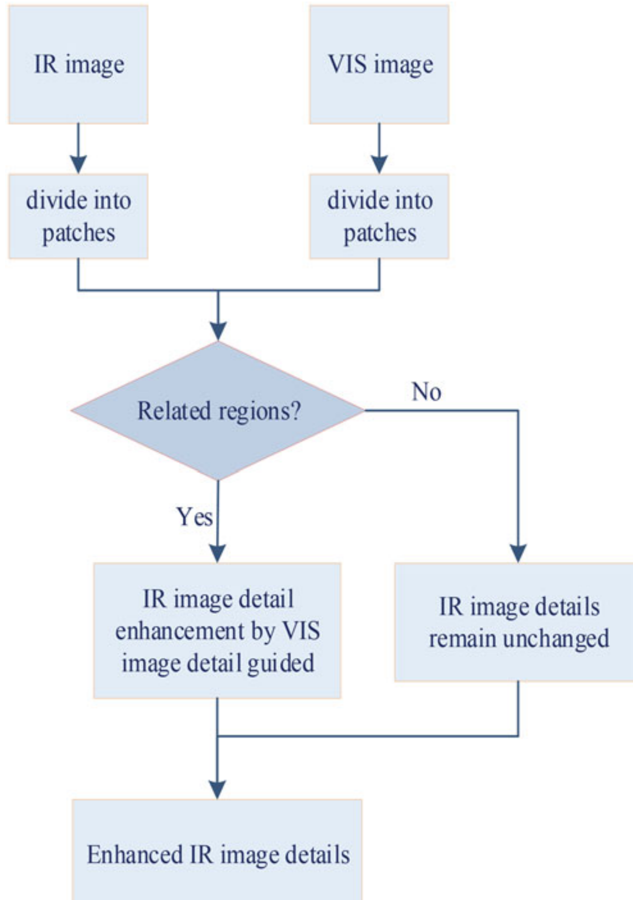

Figure 9. Process of enhancement with detail guided.

The cumulative histogram $F_T(l)$ can be defined as

$$F_T(l) = \sum\nolimits_{j=0}^{l} P_T(j), \quad 0 \le l \le 255. \tag{7}$$

The result can be defined as

$$D_T(l) = \left[\frac{255F_T(l)}{F_T(255)}\right], \quad 0 \le D_T(l) \le 255. \tag{8}$$

where $[\cdot]$ denotes the truncation of the integer.

2.4.1. Image reconstruction

The final result I_{IRE} can be derived by enhanced illuminance and reflectance component as:

$$I_{\mathrm{IRE}} = R_{\mathrm{IRCNLE}} \times L_{\mathrm{IRE}}, \tag{9}$$

where L_{IRE} means the enhanced IR illuminance component through APFHE. R_{IRCNLE} represents the enhanced reflectance component.

3. Experimental results and analysis

The images used for the experiments are from www.imagefusion.org. The IR images and VIS images are captured under same scene. In this article, we selected four original images with different scenes. There are five methods, i.e., HE, SSR, MSR, MSRCR, and AHPBC, are employed for assessing the proposed method.

3.1. Subjective analysis

Figure 10 shows five IR images with their registered VIS images, where the VIS images 1, 4 are clearer than others. The VIS image 3, 5 are poor in detail and clarity, and the VIS image 2 is worst. Figures 11–15 shows the experimental results of five IR images and their corresponding detail maps. As can be seen from the result images of HE in the Figures 11–15, the HE can significantly improve the brightness, contrast, and enhance the edge sharpness of IR images. However, the detail in highlighted regions is missing and noise is also enhanced. For instance, the noise of the background shown in Figures 12, 13, and 15 is severe. The detail of highlighted regions in Figures 11 and 14 is absence seriously. The brightness of the result images by SSR, MSR, MSRCR is obviously enhanced, whereas the contrast is poor and the edge information is seriously deficiency. For example, shown in Figures 12 and 15 the edge between the

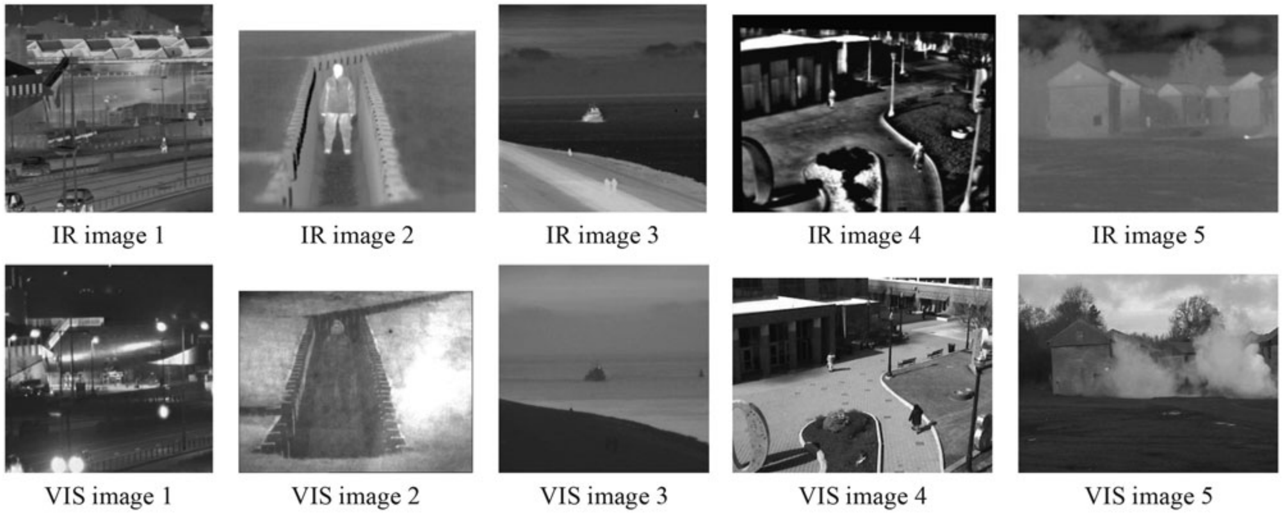

Figure 10. Four IR images with its registered VIS images.

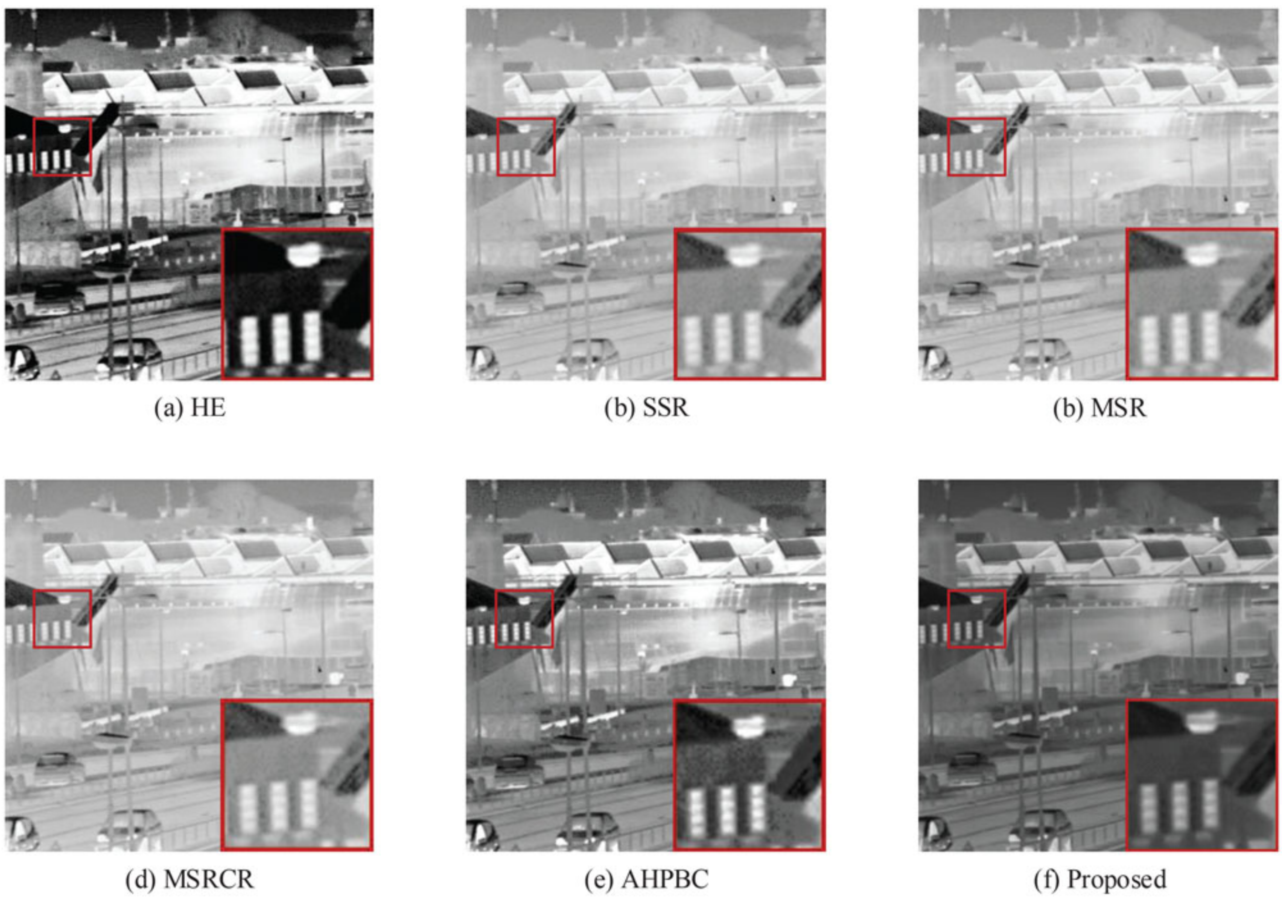

Figure 11. The experimental results of IR image 1.

people and background is obscure, especially MSR. In Figure 11, the sharpness and brightness of the IR images via AHPBC is enhanced. However, the detail is damaged, where highlighted areas in the middle of image. In Figures 11 and 13, we can see that there are many dark noises on the building and the sea, and the effect is undesirable. In addition, the overall contrast is not ideal. For the proposed method, the center playground regions in the Figure 11, the background in Figure 12, the sea in Figure 13, the pillar close to the people in Figure 14, the door and window at the middle regions in Figure 15, all surpasses other methods. It can be shown that the proposed method cannot only enhance the brightness and contrast, the image information, sharpness, and visual effect are also ameliorated.

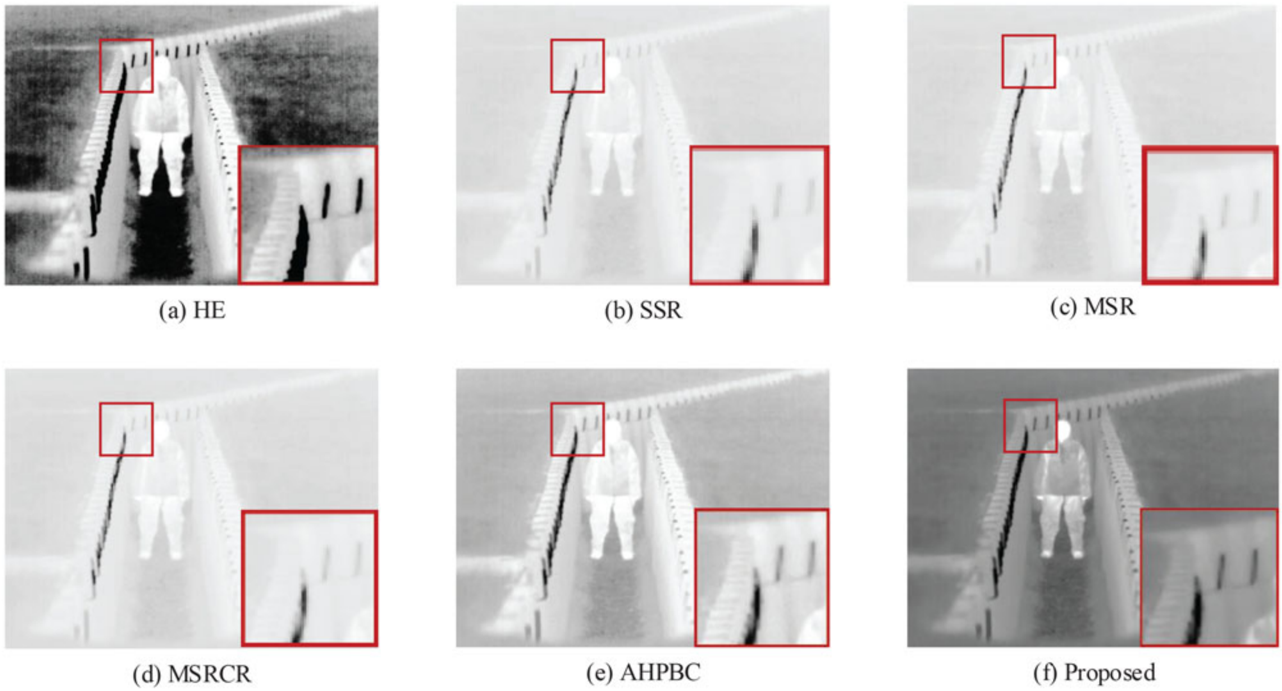

Figure 12. The experimental results of IR image 2.

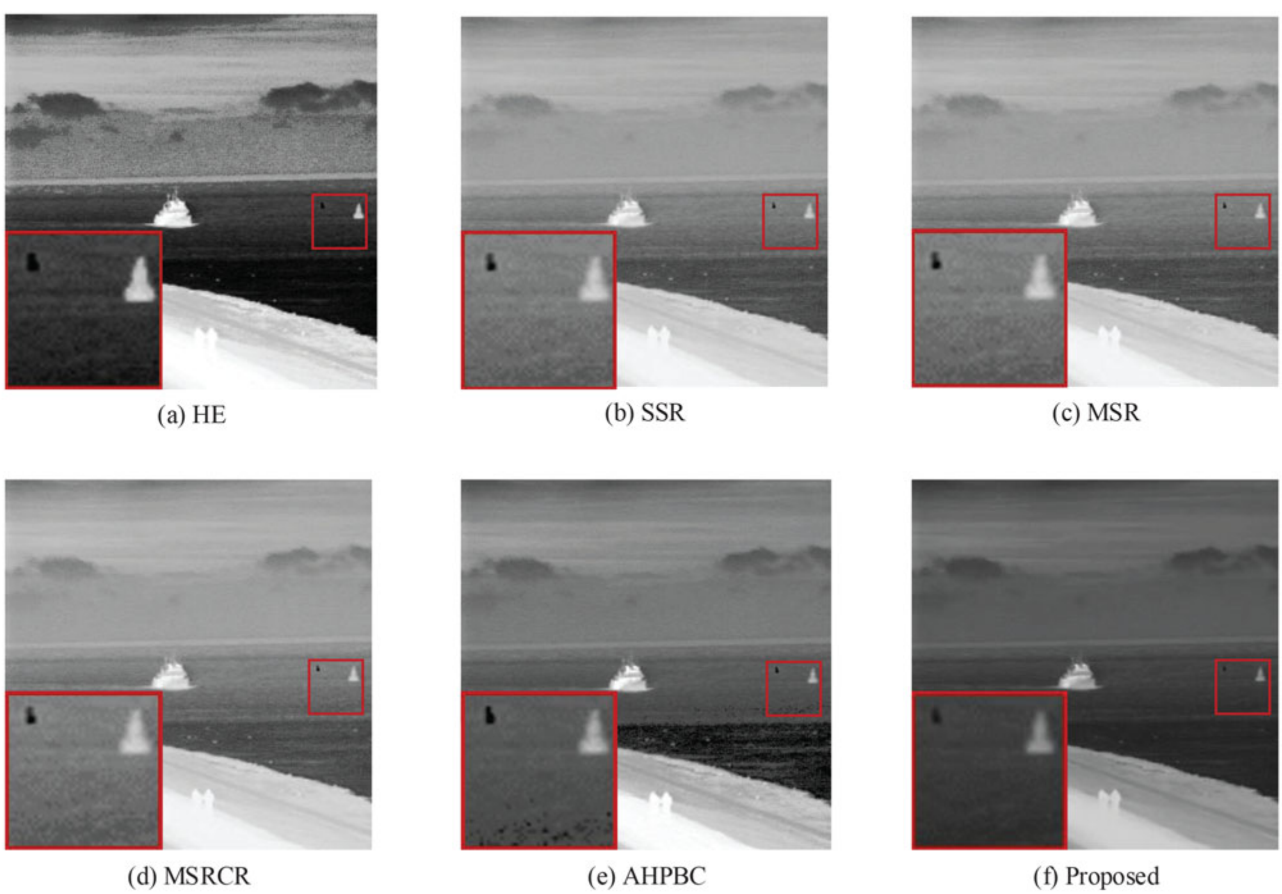

Figure 13. The experimental results of IR image 3.

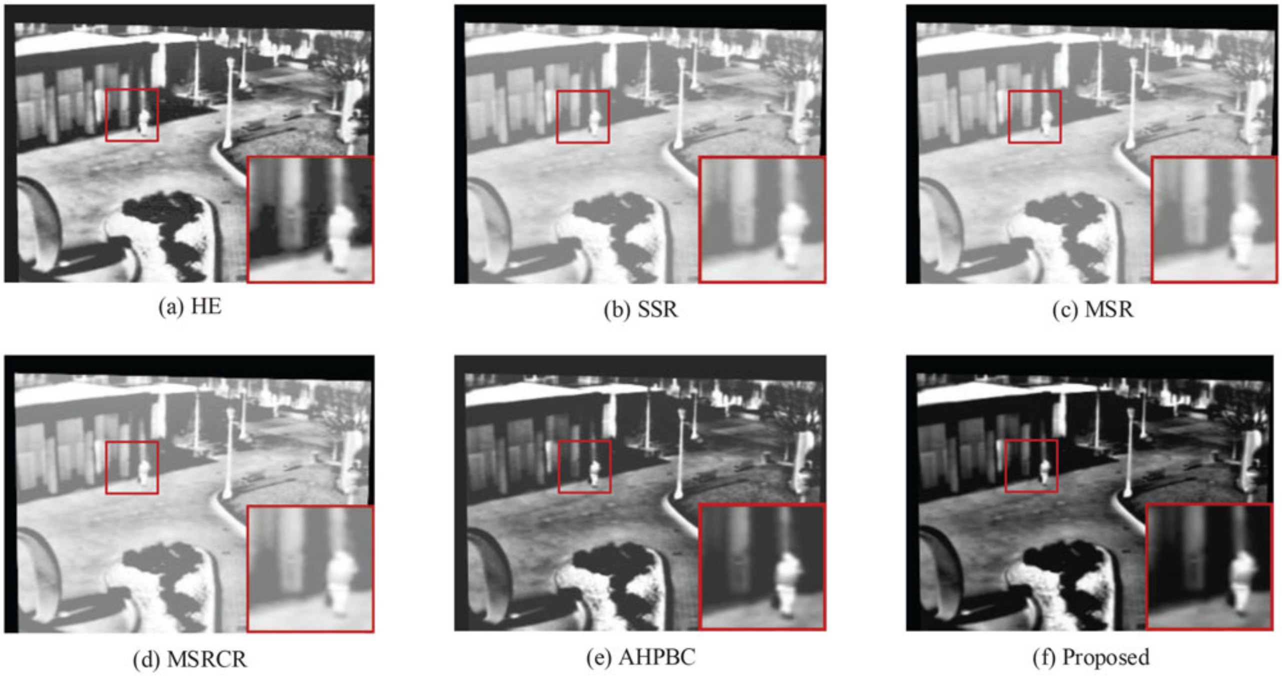

Figure 14. The experimental results of IR image 4.

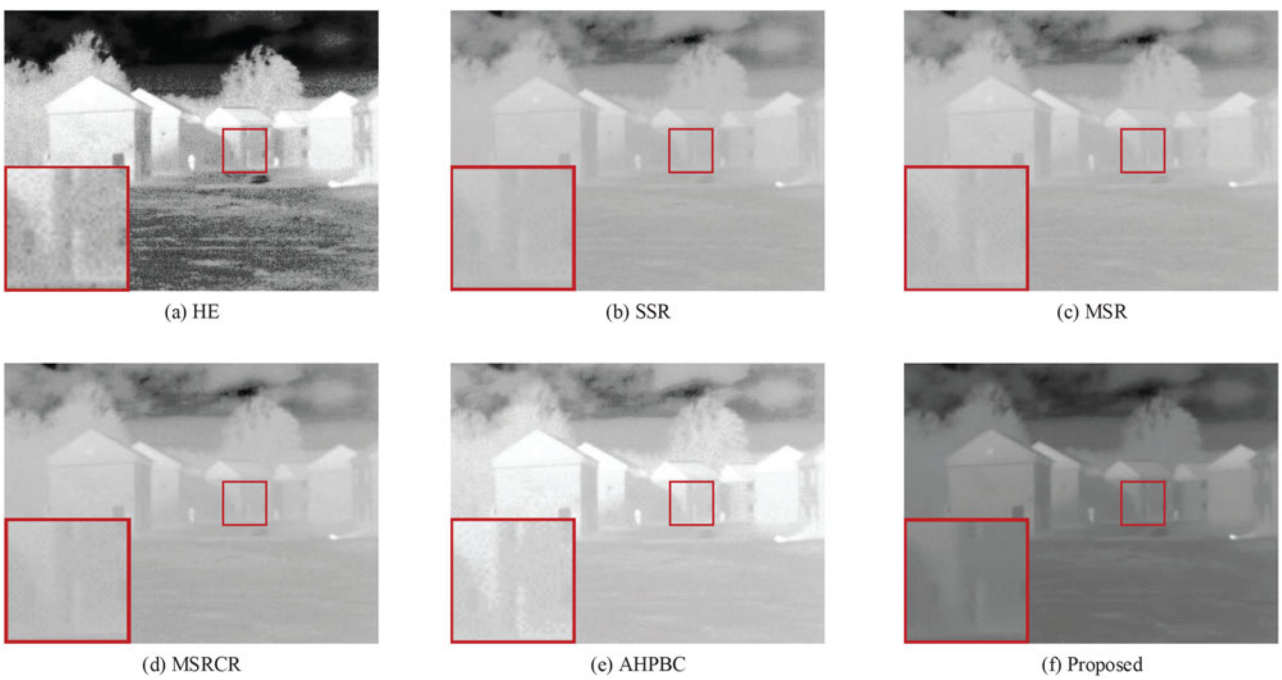

Figure 15. The experimental results of IR image 5.

3.2. Objective analysis

For objective comparison of different methods, we applied three objective metrics (Zhang, Xiong-Fei, & Jun, 2014), that are Information entropy (IE), structural similarly index (SSIM) and edge retention Q_{AB}^{F}.

IE is defined as

$$\mathrm{IE} = -\sum_{i=0}^{L-1} p_i \log_2 p_i, \tag{10}$$

where L is the number of gray levels, $p = \{p_0, p_1, \ldots, p_{L-1}\}$ denotes the gray level normalized distribution of the image. In this article, we set L is 256. IE reflects the abundance of image information.

SSIM can be expressed as

$$\mathrm{SSIM}(A,B) = [l(A,B)]^{\alpha}[c(A,B)]^{\beta}[s(A,B)]^{\gamma}, \tag{11}$$

$l(A, B)$, $c(A, B)$, and $s(A, B)$ are the brightness similarity, contrast similarity, and structural similarity, respectively. α, β, and γ are the weight of the above three. SSIM is used to measure the degree of the structural similarity preserved in the enhanced image.

Q^{F}_{AB} is applied to measure the amount of transfer of edge information which transferred from the source images to the result image. Q^{F}_{AB} can be calculated as

$$Q^{F}_{AB} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(Q^{AF}(i,j)w^{A}(i,j) + Q^{BF}(i,j)w^{B}(i,j)\right)}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(w^{A}(i,j) + w^{B}(i,j)\right)}, \tag{12}$$

where

$$Q^{XY}(i,j) = Q^{XY}_{g}(i,j) + Q^{XY}_{\alpha}(i,j),$$

$Q^{XY}_{g}(i,j), Q^{XY}_{g}(i,j)$ are the edge intensity and direction similarity of images X and Y, respectively. $w^{A}(i,j)$ and $w^{B}(i,j)$ are the weights of $Q^{AF}(i,j)$ and $Q^{BF}(i,j)$ in turn.

Table 1 lists the IE of the results by different methods. For HE, the image information is deficiency in the process of enhancement. SSR, MSR, and MSRCR can retain the image information when enhancing visual effects. AHPBC and the proposed method can effectively enhance the image information. The information entropy of the proposed method is superior to others, which can prove that VIS images can effectively guide IR images enhanced.

The results of the structural similarity index are shown in Table 2. The more similar the source image is, the better the quality of result images. The SSIM values of HE are the lowest and the visual effect is also unsatisfactory as seen in Figures 11–15. Compared with HE, the other methods can retain the structural information of the original images, and the brightness and sharpness are also increased. For the proposed method, the structural similarity index is better than other methods. The proposed method can effectively remove image noise and preserve detail information, as well as enhance image sharpness and texture detail.

The results of Q^{F}_{AB} are shown in Table 3. The value of Q^{F}_{AB} indicate the degree of edge information transferred from original images. The values of HE are lower than others. That is the edge information of result image of HE is the least. Compared the values among SSR, MSR, and MSRCR, the difference in edge information is diminutive. For AHPBC, it is superior to the others, effectively enhancing contrast and brightness while preserves edge information. The value of the proposed method is generally higher than other methods. That can explain that the proposed method has certain advantages for retaining the edge information of the original image.

In summary, from the overall results of objective analysis, the proposed method utilizes the VIS image to enhance the IR image and successfully enhances the details, contrast, and sharpness of IR images.

Table 1. Evaluation of information entropy (IE).

IE	HE	SSR	MSR	MSRCR	AHPBC	Proposed
Image 1	4.463	4.759	5.266	5.261	4.479	**5.968**
Image 2	6.510	6.506	6.604	6.615	6.515	**6.682**
Image 3	6.536	6.312	6.313	6.308	6.599	**6.659**
Image 4	6.787	5.451	5.461	5.470	6.964	**7.071**
Image 5	6.502	5.965	5.993	6.004	6.558	**6.736**

Note: The better results are marked with bold numbers.

Table 2. Evaluation of structural similarity index (SSIM).

SSIM	HE	SSR	MSR	MSRCR	AHPBC	Proposed
Image 1	0.273	0.712	0.706	0.705	0.313	**0.765**
Image 2	0.275	0.286	0.286	0.287	0.428	**0.784**
Image 3	0.354	0.487	0.490	0.491	0.462	**0.681**
Image 4	0.447	0.588	0.588	0.589	0.664	**0.676**
Image 5	0.307	0.350	0.350	0.351	0.425	**0.615**

Note: The better results are marked with bold numbers.

Table 3. Evaluation of edge retention (Q^{F}_{AB}).

Q^{F}_{AB}	HE	SSR	MSR	MSRCR	AHPBC	Proposed
Image 1	0.225	**0.508**	0.507	0.504	0.258	0.456
Image 2	0.287	0.474	0.474	0.475	0.591	**0.602**
Image 3	0.247	0.446	0.445	0.444	0.362	**0.463**
Image 4	0.258	0.202	0.201	0.202	**0.480**	0.404
Image 5	0.255	0.332	0.331	0.334	0.564	**0.608**

Note: The better results are marked with bold numbers.

3.3. Analysis of enhancement with the help of VIS image

To prove the effectiveness of the proposed method, we present a comparison experiment in this section: enhancement without VIS image, enhancement with the help of VIS image at related regions of an image, and enhancement with the help of VIS image in all regions of an image. In Figures 16–18 show their experimental results, respectively.

As shown as the renderings of contrast experiment, the effect of enhancement with detail guided at related regions significantly outperforms the effect of enhancement without detail guided. When all details of images are guided enhanced, the information of VIS images appears in the enhanced image. In Figure 18(a) the detail of the middle of the hull in the IR image 1, Figure 18(b) the detail of the ground well, the vehicles and the nest iron fence of image 2 all contain the information of VIS image and result in the distortion of IR image.

Through the subjective and objective aspects, and detail guide enhanced analysis for the above experimental results of each enhancement method. The proposed method in this article can effectively improve the edge and contour detail of the image

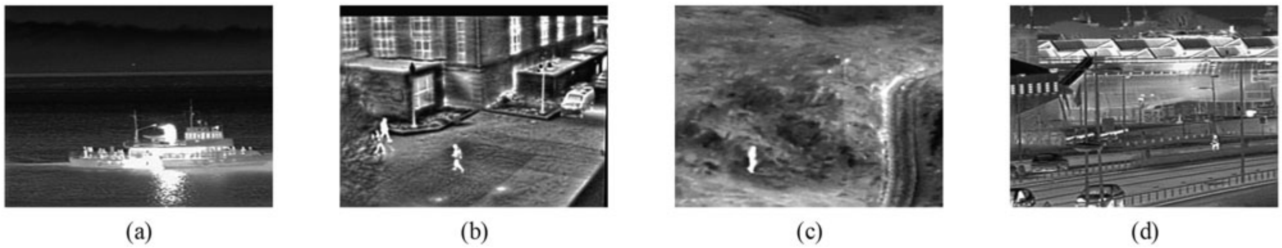

Figure 16. The results of enhancement without detail guided.

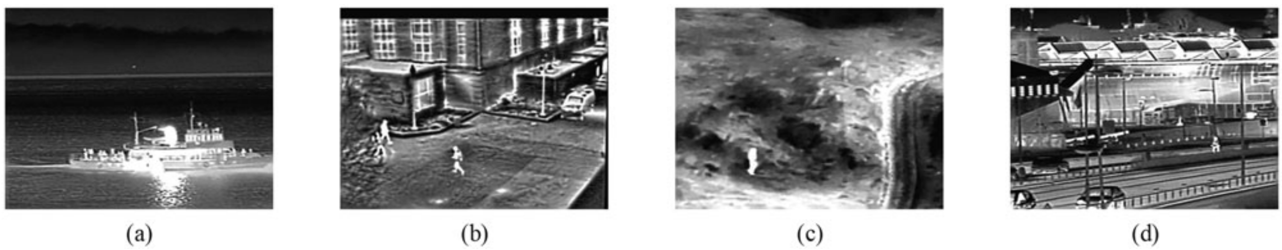

Figure 17. The results of enhancement with detail guided at related regions.

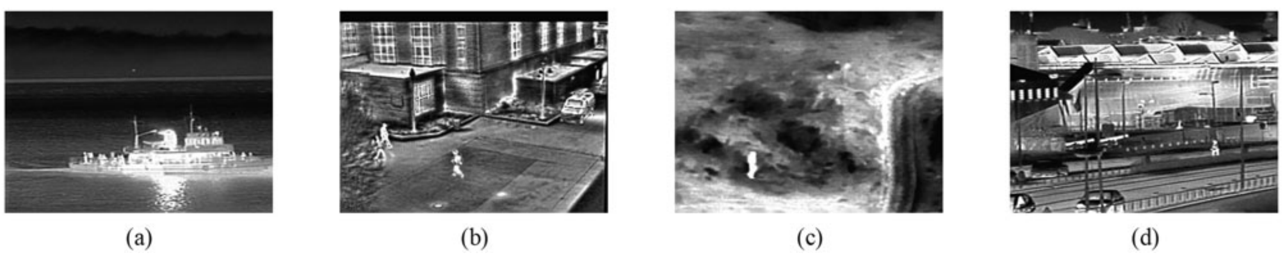

Figure 18. The results of enhancement with all detail guided.

when enhancing the contrast and detail information of the infrared image and improving the visual effect, and the target details are outstanding.

4. Conclusion

In this article, we present a multi-sensor IR image enhancement method based on correlation measurement of the VIS image for human-centric computing. Applying the correlation between the IR and VIS images to enhance the weak edge outline and detail of the IR images. IR image enhancement with the help of VIS images was explored initially. Experimental results show that the subjective and objective effects of the method are higher than of other methods. The proposed method in this article can effectively enhance the infrared information and sharpness and improve the visual effect when the VIS clarity is better than the IR clarity.

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