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Infrared image detail enhancement approach based on improved joint bilateral filter

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ABSTRACT

In this paper, we proposed a new infrared image detail enhancement approach. This approach could not only achieve the goal of enhancing the digital detail, but also make the processed image much closer to the real situation. Inspired by the joint-bilateral filter, two adjacent images were utilized to calculate the kernel functions in order to distinguish the detail information from the raw image. We also designed a new kernel function to modify the joint-bilateral filter and to eliminate the gradient reversal artifacts caused by the non-linear filtering. The new kernel is based on an adaptive emerge coefficient to realize the detail layer determination. The detail information was modified by the adaptive emerge coefficient along with two key parameters to realize the detail enhancement. Finally, we combined the processed detail layer with the base layer and rearrange the high dynamic image into monitor-suited low dynamic range to achieve better visual effect. Numerical calculation showed that this new technology has the best value compare to the previous research in detail enhancement. Figures and data flowcharts were demonstrated in the paper.

1. Introduction

Infrared imaging has been applied in various fields for both military and civilian use, such as design, test, manufacturing, chemical imaging, night vision, surveillance in security, target signature measurement, tracking and so on [1,2,9–12]. Normally the infrared cameras have a wide dynamic range more than 14-bit. The usual way to display the infrared images on a screen is to compress them with a histogram equalization algorithm. However this method cannot fully show the entirely detail information. In recent years, many approaches have been widely investigated with a number of detail enhancement techniques proposed in literature [3,4,13–16]. All these methods aim to enhance the quality of an infrared image and reproduce the reality of the captured scene or target as possible as they could.

There are many classic edge extraction operators for enhancing an image. These operators make the edge sharper or the details of an image extruder, such as Sobel [5–7], Prewitt [17,18], Log [19,20], Laplacian [20] and so on. However the results were not satisfied. The real problem for the researchers is that how we can fully spot out the very tiny fluctuation of the gray value of an infrared image. However, the traditional methods can only simply watch the approximate morphology of an image, but not the total content in it. Many researchers focused on figuring out the solution. For example, in 2011, Zuo et al. [8] proposed a novel method of reality reproduction for high-dynamic-range infrared images called BF&DDE, which worked better in detail enhancement and noise reduction than other methods. This approach used a modified bilateral filter to separate a raw image into detail layer and base layer. The base layer is histogram equalized to fit in the display range, while the detail layer is added back after an adaptive gain control process. In 2014, we proposed a method to achieve this goal called the GIF&DDE [21–23] in which a guided image filter was used to separate the raw image. Both these two methods could greatly increase the image quality and enhance the image into a whole new level for visual observation. However these two methods have certain drawbacks. For example, the generic problem exists in these two methods are the reversal artifacts. When the image has too many strong edges in it, both these methods cannot fully eliminate them. In GIF&DDE, this could happen because the principle of the filter itself. Since GIF is a linear filter, it is surely hard to deal with high gradient information within the edges. In BF&DDE, Zuo [8] uses adaptive Gaussian filter to suppress the gradient reversal effect with a big filter window, if the edges are too strong, the size of the filter window usually bigger than 15×15, which could be time-consuming. In our further research, we find that these two methods still can be improved in enhancing the digital details within the image scene. Thus, we have figured out a way to do so in this paper. This method is inspired by the

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joint-bilateral filter [24] which is usually used in color image process. We use two adjacent infrared images in the video sequence to calculate the detail layer and get a better detail content. We also design a novel kernel function to calculate with the joint-bilateral filter during the processing procedure. This kernel function is sensitive to the gradient structure within the image, which could be given better elimination of the reversal artifacts. The proposed method can be more flexible of reducing the background noises. This method can achieve the greater effect of detail enhancement and noise reduction, and furthermore, works better near strong edges.

The paper is organized as follows: in Section 2, the detailed mechanism of the proposed method is introduced; in Section 3, the experimental results are introduced; in Section 4, we give a conclusion of our method.

2. The mechanism of the proposed algorithm

2.1. The principle of the joint-bilateral filter

Kopf et al. [24] proposed the joint-bilateral filter (JBF) in 2007, which was first used in processing the colored images. They used the high resolution colored image as the reference image, and used the JBF to up-sample the low resolution image in order to improve the resolution. In our research, we find this procedure is also very effective when dealing with the infrared images. The basic difference is that, we do not up-sample the original image, but choose two adjacent infrared images as a pair, and use the first image as the basic image while the second one as the reference image. We use the JBF to calculate the kernel function inside the two images, and then applied the kernel on the reference image to get the filtered result. The filtered result could be treated as the base layer of the basic image, which is used to determine the detail layer by a simple subtraction with the reference image. We also design an effective filter coefficient to deal with the gradient reversal artifacts which happens in using the non-linear filter to process the original image [9,10]. This approach is proved better and faster than the Gaussian filter mentioned in the BF&DDE [8]. Finally, we combine the processed detail layer and the base layer back together to achieve the goal of detail enhancement of the infrared image. Fig. 1 gives an illustration of the mechanism of the proposed algorithm.

The expression of joint-bilateral filter is given as Eq. (1). The primary difference between the joint-bilateral filter and the traditional bilateral filter is that the JBF uses two adjacent images as the input, and then calculate the kernel weights matrix [24].

$$I_{JBF} = k \sum_{i',j' \in \Omega} \omega_s(\|i-i',j-j'\|)\omega_r(\|I_B - I_R\|)I_R \tag{1}$$

Where the I_{JBF} is the JBF filtered result, I_R is the reference image, I_B is the basic image. Ω is the size of the filter window. k is the normalization term:

$$k = \sum_{i',j' \in \Omega} \omega_s(\|i-i',j-j'\|)\omega_r(\|I_B - I_R\|) \tag{2}$$

The notation $i',j' \in \Omega$ denotes that (i',j') and (i,j) are corresponding pixels from the adjacent frames. ω_s, ω_r are two Gaussian kernels, in which ω_s is the kernel of spatial domain and ω_r is the kernel of intensity domain. The two Gaussian kernels could be expressed by the following equations:

$$\omega_r(I_B, I_R) = \exp\left(-\frac{\|I_B - I_R\|^2}{2\sigma_r^2}\right) \tag{3}$$

$$\omega_s((i,i'),(j,j')) = \exp\left(-\frac{\|(i-i')-(j-j')\|^2}{2\sigma_s^2}\right) \tag{4}$$

where σ_r and σ_s are the standard deviation of spatial and intensity. The two parameters define the extension of the two Gaussian kernels. σ_s determines the size of the considered corresponding pixel pairs in the adjacent images and should be proportional to the image size. σ_r determines the minimum amplitude of an edge. Since the adjacent images are very similar to each other, if the variation amplitude in the two images is less than σ_r, it will be smoothed by the JBF and the variation will leak into the detail layer. If the variation is sharper than σ_r, it will be less altered by the filter. The selection of these two parameters are very crucial for acquiring the best quality of the detail layer.

After the separation by the JBF, we can get the base layer and the detail layer noted as I_{JBF} and I_d, respectively. I_R is the reference image. The detail layer can be subtracted by the reference image and the base layer:

$$I_d = I_R - I_{JBF} \tag{5}$$

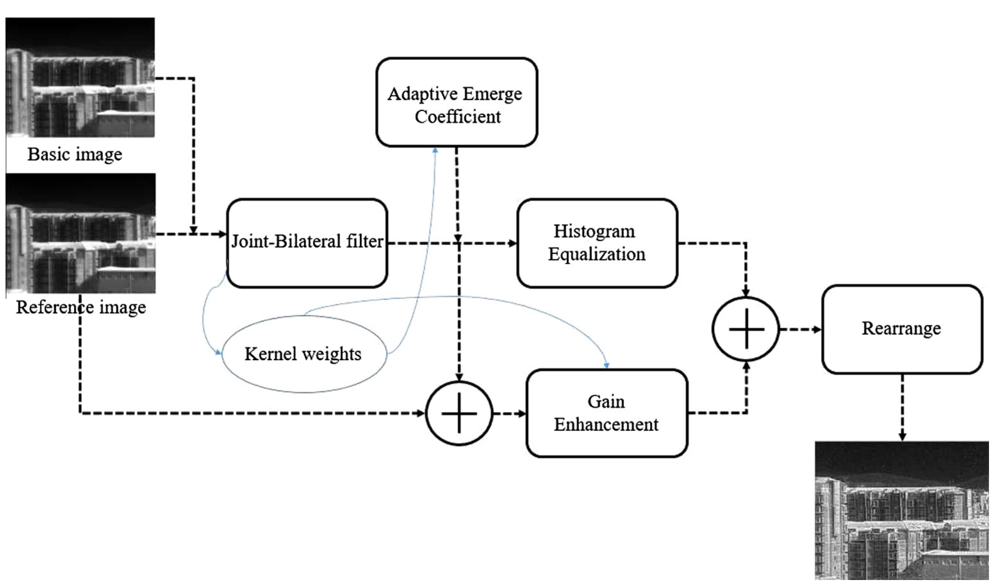

Fig. 1. The scheme of the proposed algorithm. Blue arrows indicates that these modules are controlled or can be adjusted by the kernel weights. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)