An improved adaptive preprocessing method for TDI CCD images*

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In order to achieve high quality images with time-delayed integration (TDI) charge-coupled device (CCD) imaging system, an improved adaptive preprocessing method is proposed with functions of both denoising and edge enhancement. It is a weighted average filter integrating the average filter and the improved range filter. The weighted factors are deduced in terms of a cost function, which are adjustable to different images. To validate the proposed method, extensive tests are carried out on a developed TDI CCD imaging system. The experimental results confirm that this preprocessing method can fulfill the noise removal and edge sharpening simultaneously, which can play an important role in remote sensing field.

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Unlike conventional charge-coupled device (CCD), the time-delayed integration (TDI) CCD is a kind of linear array photoelectric detector, which implements charge accumulation by superposition mode[1]. It has advantages of high sensitivity, high dynamic range and low noise. Therefore, TDI CCD is applied widely in aerospace photography, remote sensing, industry measurement and other fields[2,3]. Especially in remote sensing field, it can make the aerospace camera lighter and smaller, due to its high sensitivity.

There are many kinds of noises interfering the TDI CCD imaging system, such as photon shot noise, dark current noise, electric and thermal noise, and so on[3]. The images acquired by the system will contain the noises above, leading to the affection of their final display quality, but high-quality images possess more abundant information and higher value. Consequently, we usually apply some preprocessing methods to improve the display quality by denoising and edge sharpening.

At present, there are many preprocessing methods, which can be divided into two categories. One is based on spatial domain, for example, the adaptive noise smoothing filter, Wiener filter, bilateral filter, and so on[4-7]. The other is based on transform domain, including discrete wavelet transform (DWT), discrete cosine transform (DCT), block-matching and three-dimensional (BM3D) filter, etc[8-10]. By contrast, the former is easier to be implemented with no transform. They can smooth the noise effectively, but most just try to preserve the edge information in the image, unable to enhance it. Although an algorithm combining the bilateral filter and the unsharp masking filter can sharpen the edges, presented in Ref.[6], the resultant images are not satisfactory due to its sensitivity to the noise, producing the overshoot and undershoot artifacts.

Therefore, a preprocessing method in spatial domain, called improved adaptive low-pass (IALP) filter, is proposed to implement the image denoising and edge enhancement. It is a kind of weighted average filter, which integrates the average filter and the improved range filter with advantages of low complication, easy implementation and strong practicability. Its working principle is similar to that of Wiener filter, which is based on the minimum mean square error (MMSE) theory.

Wiener filter is one of the classical algorithms in spatial domain. Its filtering principle is

$$\hat{g}[m,n]=\frac{\sigma_{\mathrm{n}}^{2}}{\sigma_{\mathrm{I}}^{2}}\times\bar{g}[m,n]+\frac{\sigma_{\mathrm{I}}^{2}-\sigma_{\mathrm{n}}^{2}}{\sigma_{\mathrm{I}}^{2}}\times g[m,n]\,, \tag{1}$$

where $g[m,n]$ is the intensity of pixel at $[m,n]$ and $\bar{g}[m,n]$ is the average intensity of pixels in the $M\times N$ window centered at $[m,n]$. σ_{n}^{2} and σ_{I}^{2} represent the variances of the noise and the actual image, respectively. Through analyzing Eq.(1), we can see that Wiener filter is an edge-preserving smoothing filter with advantage of good adaption, but its lack lies in that it just tries to preserve the edges, instead of enhancing them. Besides,

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it needs to calculate the variance σ_{n}^2, but the accurate noise variance is usually determined through a lot of experiments[11-13]. It is difficult to implement an accurate and efficient processing algorithm.

To further improve the performance of the filter, firstly, we introduce an improved range filter proposed in Ref.[7]. A conventional range filter is a kind of low-pass Gaussian filter, whose weighted factor can be expressed as

$$W_{\mathrm{r}}[m_0,n_0;m,n]=\exp\left[-\frac{(g[m,n]-g[m_0,n_0])^2}{2\sigma_{\mathrm{r}}^2}\right], \quad (2)$$

where $[m_0,n_0]$ is the central pixel of the window, $\Omega_{m_0,n_0}=\{[m,n]:[m,n]\in[m_0-M,m_0+M]\times[n_0-N,n_0+N]\}$, and σ_{r}^2 is the variance of the Gaussian filter. It can be seen that the range filter gives higher weight to pixels that are similar to the center pixel in gray value. If we add a variable $\varepsilon[m_0,n_0]$, an offset of the central pixel $[m_0,n_0]$, Eq.(2) becomes

$$W_{\mathrm{r}}^{'}[m_0,n_0;m,n]=\exp\left[-\frac{(g[m,n]-g[m_0,n_0]-\varepsilon[m_0,n_0])^2}{2\sigma_{\mathrm{r}}^2}\right]. \quad (3)$$

Then we can see that the filter gives higher weight to pixels that are similar to the intensity $(g[m_0,n_0]+\varepsilon[m_0,n_0])$. That is the principle of the improved range filter, which can be applied to the edge sharpness implementation. According to the analysis above, we can construct the IALP filter based on the average filter and the improved range filter. Its principle can be expressed as

$$\hat{g}^{'}[m,n]=a\times g_{\mathrm{r}}[m,n]+b\times\bar{g}[m,n], \quad (4)$$

where $g_{\mathrm{r}}[m,n]$ is the output of the improved range filter for pixel $[m,n]$. The parameters a and b are the weighted factors. They should be normalized and adjustable according to different image data, for example, a flat patch or a high variance one.

To achieve the goals above, we seek a solution to determine the reasonable weighted factors. Specifically, we minimize the following cost function in the window $\Omega[m_0,n_0]$ to minimize the difference between $\hat{g}^{'}[m,n]$ and $g[m,n]$:

$$\{a^*,b^*\}=\arg\min_{\{a,b\}}\sum\left[(a\times g_{\mathrm{r}}[m,n]+b\times\bar{g}[m,n]-g[m,n])^2+\epsilon a^2\right], \quad (5)$$

where ϵ is a regularization parameter. We will discuss its specific meaning in the following part. Eq.(5) is a linear ridge regression model and its solution can be given by

$$\begin{cases} a^*=\dfrac{\sigma_{\mathrm{I}}^2}{\sigma_{\mathrm{I}}^2+\epsilon}, \\ b^*=1-a^*=\dfrac{\epsilon}{\sigma_{\mathrm{I}}^2+\epsilon}. \end{cases} \quad (6)$$

Consequently, taking Eq.(6) into Eq.(4), we can obtain the formula:

$$\hat{g}^{'}[m,n]=\frac{\sigma_{\mathrm{I}}^2}{\sigma_{\mathrm{I}}^2+\epsilon}\times g_{\mathrm{r}}[m,n]+\frac{\epsilon}{\sigma_{\mathrm{I}}^2+\epsilon}\times\bar{g}[m,n]. \quad (7)$$

We can achieve the weighted factors according to the image variance σ_{I}^2 and the parameter ϵ, independent of σ_{n}^2, unlike Wiener filter. Once we know the output of $g_{\mathrm{r}}[m,n]$, we can perform the image filtering by means of Eq.(7).

The specific calculation expression of $g_{\mathrm{r}}[m,n]$ is

$$g_{\mathrm{r}}[m,n]=\sum_k\sum_l h[m,n;k,l]g[k,l], \quad (8)$$

where $h[m,n;k,l]$ is the response at $[m,n]$ to an impulse at $[k,l]$. Its definition is

$$h[m_0,n_0;m,n]=r_{m_0,n_0}^{-1}W_r^{'}[m_0,n_0;m,n], \quad (9)$$

$$r_{m_0,n_0}=\sum_{m=m_0-M}^{m_0+M}\sum_{n=n_0-N}^{n_0+N}W_{\mathrm{r}}^{'}[m_0,n_0;m,n], \quad (10)$$

where r_{m_0,n_0} is a normalization factor that assures that the filter preserves average gray value in constant areas of the image.

To sharpen the edges in the image, we need to choose a reasonable offset $\varepsilon[m_0,n_0]$. If $\varepsilon[m_0,n_0]=MEAN-g[m_0,n_0]$, where *MEAN* denotes the average intensity of pixels in Ω_{m_0,n_0}, the output $g_{\mathrm{r}}[m_0,n_0]$ will shift towards the *MEAN*, resulting in a blurred image. If $\varepsilon[m_0,n_0]=g[m_0,n_0]-MEAN$, the output $g_{\mathrm{r}}[m_0,n_0]$ will shift away from the *MEAN* to sharpen the image. Therefore, we set the offset as $\varepsilon[m_0,n_0]=g[m_0,n_0]-MEAN$, and Eq.(3) can be rewritten as

$$W_{\mathrm{r}}^{'}[m_0,n_0;m,n]=\exp\left\{-\frac{[g[m,n]-(2\times g[m_0,n_0]-MEAN)]^2}{2\sigma_{\mathrm{r}}^2}\right\}. \quad (11)$$

The performance of the IALP filter can be analyzed in two cases according to Eq.(7).

Case 1: "edge region." The image changes a lot within Ω_{m_0,n_0}. The variance σ_{I}^2 is far bigger than ϵ, $\sigma_{\mathrm{I}}^2>>\epsilon$, and we can get $\frac{\sigma_{\mathrm{I}}^2}{\sigma_{\mathrm{I}}^2+\epsilon}\approx 1$ and $\frac{\epsilon}{\sigma_{\mathrm{I}}^2+\epsilon}\approx 0$, so $\hat{g}^{'}[m,n]\approx g_{\mathrm{r}}[m,n]$. That means it can sharpen the edges in the image.

Case 2: "uniform region." The variance σ_{I}^2 is far smaller than ϵ, $\sigma_{\mathrm{I}}^2<<\epsilon$, and we can get $\frac{\sigma_{\mathrm{I}}^2}{\sigma_{\mathrm{I}}^2+\epsilon}\approx 0$ and $\frac{\epsilon}{\sigma_{\mathrm{I}}^2+\epsilon}\approx 1$, so $\hat{g}^{'}[m,n]\approx\bar{g}[m,n]$. That means it turns out to be an average filter to smooth the noise in the image.

More specifically, the parameter ϵ is a criterion that determines an edge region or a uniform one. The regions with variance σ_{I}^2 much smaller than ϵ are smoothed, whereas those with variance much larger than ϵ are enhanced. The effect of ϵ in the IALP filter is similar to the range variance σ_{r}^2, both of which determine where an edge region is, which should be enhanced. They are equivalent, so we can set $\epsilon=\sigma_{\mathrm{r}}^2$.

Consequently, the IALP filter is able to smooth the noise and enhance the edges in the image simultaneously. In addition, there is no need to calculate the variance of the noise σ_{n}^2, compared with Wiener filter, which can obviously reduce the amount of experiments and computation. In order to further emphasize the expected effect of smoothing or edge sharpening, we introduce the parameter k, then Eq.(7) turns out to be

$$\hat{g}'[m,n]=\frac{k\sigma_{\mathrm{l}}^2}{k\sigma_{\mathrm{l}}^2+\epsilon}\times g_{\mathrm{r}}[m,n]+\frac{\epsilon}{k\sigma_{\mathrm{l}}^2+\epsilon}\times\bar{g}[m,n], \quad (12)$$

where k is a non-negative number. If k>1, the function of edge sharpening will be enhanced with that of smoothing decreasing, else, on the contrary. Then we can apply the IALP filter to process images in terms of Eq.(12). A TDI CCD imaging system is developed and its main technical specifications are indicated in Tab.1.

Tab.1 Technical specifications of the imaging system

Items	Specifications
Spectral range	450—800 nm
Pixel size	8.75 μm×8.75 μm
Spatial pixels	4 096
Optional stages	8,16,32,48,72,96
PGA (programmable gain amplifier)	0—36 dB

Then we employ the imaging system to acquire multiple images with different targets, and choose two of them with size of 256×256 pixels to validate the performance of the proposed method. The M×N window should be appropriate in size. If it is too small, it will not be able to cover most of the edge transitions. On the other hand, if it is too big, it might increase the computation and consume a lot of time. So a 7×7 window is chosen, which satisfies all the considerations. The standard deviation (STD) σ_{r} of the improved range filter determines how selective the filter is in choosing the pixels that are similar enough in gray value. In our experiments, σ_{r} is set to 2. So the parameter ϵ=2 and we set k=2 in the following tests to obtain a better edge-sharpening image. Fig.1 is the raw image for target1 "building", which is restored by Wiener filter and IALP filter, respectively, as shown in Fig.2 and Fig.3. The gray level distributions for edge C are depicted in Fig.4.

Compared with Fig.1 visually, Fig.2 preserves the major edge information effectively, instead of enhancing it. Fig.3 shows that the edges have been sharpened clearly. Fig.4 presents the gray level distributions for edge C under three conditions. It can be seen that the gray scale gradient of the edge restored by IALP increases effectively, bigger than that of the original, by appropriate adjustment of the gray level. However, the gray scale gradient decreases in the image restored by Wiener. Thus the proposed method can sharpen the edge information. We can analyze the data enclosed in the boxes A and B, size of 25×25 pixels, representing the uniform region and the edge region. The comparison results are reported in Tab.2.

Fig.1 The raw image for target1

Fig.2 The image for target1 restored by Wiener filter

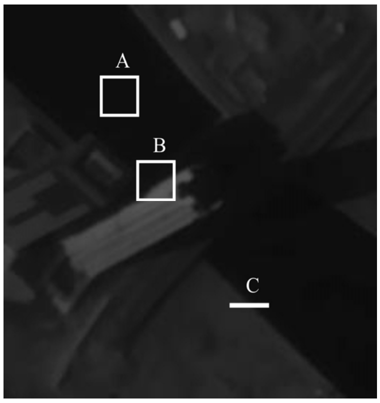

Fig.3 The image for target1 restored by IALP filter

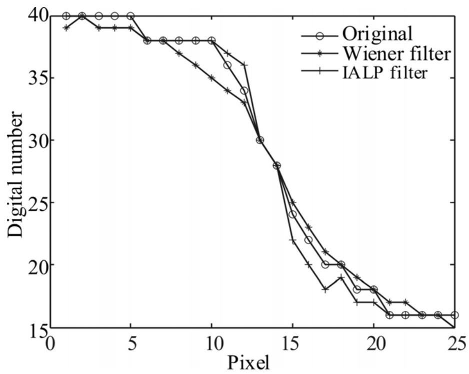

Fig.4 The gray level distributions for edge C

Tab.2 The comparison results for image of target1

Objects	Box A (digital number)		Box B (digital number)	
	Average intensity	Standard deviation	Average intensity	Standard deviation
Raw data	14.04	0.30	39.37	27.24
Data restored by Wiener filter	14.01	0.12	39.30	26.48
Data restored by IALP filter	14.01	0.12	39.33	28.59

We can see that the average intensities restored by the two methods are nearly the same as the raw data, because both filters have performed the normalization processing. Compared with the raw data, the STDs for Wiener filter and IALP filter in box A decrease, indicating the effect of smoothing, and they are close to each other. For the STD in box B, the image data restored by Wiener filter is smaller than the raw data, due to the edge preserving. Unlike Wiener, the STD of the image data restored by IALP is bigger than that of the raw data, indicating the effect of edge sharpness and illustrating the analysis above.

Then we use another image to further validate the proposed method. Fig.5 is the raw image for target2 "beach". Fig.6 and Fig.7 are the restored images by Wiener filter and IALP filter, respectively. The distributions of the gray level for edge F are shown in Fig.8.

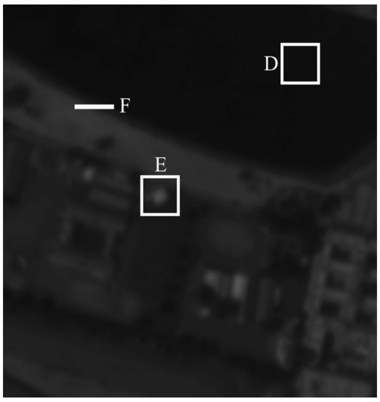

Fig.5 The raw image for target2

Fig.6 The image for target2 restored by Wiener filter

Fig.7 The image for target2 restored by IALP filter

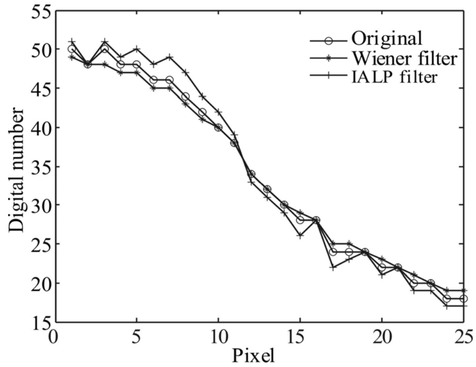

Fig.8 The gray level distributions for edge F

Similarly, we can see that Fig.6 just preserves the major edge information without enhancing it, compared with Fig.5, whereas the edges have been sharpened clearly in Fig.7. The gray scale gradient of the edge F restored by IALP is bigger than that of the original, as shown in Fig.8. The data enclosed in the red box D and E are analyzed, size of 25×25 pixels, representing the uniform region and the edge region. The results are presented in Tab.3.

Tab.3 The comparison results for image of target2

Objects	Box D (digital number)		Box E (digital number)	
	Average intensity	Standard deviation	Average intensity	Standard deviation
Raw data	14.00	0.38	35.16	12.04
Data restored by Wiener filter	13.97	0.18	35.52	11.45
Data restored by IALP filter	13.98	0.18	35.20	13.40

It shows that the average intensities restored by the two methods are nearly the same. The STDs for Wiener filter and IALP filter in uniform region decrease significantly. However, for the STD in edge region, IALP filter is bigger than that of the raw data. The STD data in Tab.2 and Tab.3 describe the performance of both filters quantitatively, including the ability of smoothing in uniform region and that of sharpening in edge region. By comparing the data, we can see that the IALP filter is nearly the same with Wiener filter in the aspect of noise smoothing, but it can achieve better enhancement performance than Wiener. By combining all the analysis results, we can draw the conclusion that the IALP method is an effective filter integrating the functions of both smoothing and edge sharpening.

A preprocessing method, IALP filter, is proposed in this paper. It is a weighted average filter integrating the average filter and the improved range filter. Its weighted factors are adjustable to process different images, deduced by a cost function. Compared with conventional preprocessing methods, it can exhibit nice properties of noise smoothing and edge enhancing simultaneously. Through abundances of experiments on the developed imaging system, the performance of the proposed method is demonstrated with advantages of low complication, easy implementation and strong practicability. It can play an important role in remote sensing field to achieve high signal-to-noise ratio and high definition image data.

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