The realtime parallel system based on dual DSPs for remote sensing image restoration using time-varying wavelet packets

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ABSTRACT

Considering the fact that the remote sensing image is mainly captured by a linear CCD with the push-broom way which the image varies over time, the time-varying wavelet packets for image restoration is proposed in the paper. On one hand, the result of the method is that the problem of the correlation between the images is solved, and on the other hand, it is the method that can remarkably reduce the calculating overhead and the data throughput, which is a key innovation for a real-time system. In this paper, the optimized wavelet packet bases by double tree searching algorithm are adaptively changed in different time. To realize the algorithm, we presented a dual DSPs real-time parallel system. The parallel system based on TMS320C6416-7E3 DSP has the characteristics of modular and flexible design and maintainability. The ping-pong structure and the streamline structure are both designed in the system. According to the complexity of the algorithm and the requirement of the data throughput, one of the two parallel structures can be realized freely only by changing a bit. It can realize the restoration algorithm with 4096*4096 images in real-time by demonstrated by our experiment in practice.

Key words: image restoration, time-varying wavelet packets, DSP，parallel, C6416

1. INTRODUCTION

Restoration of blurred and noisy satellite images can be defined as the general problem of estimating a two-dimensional (2-D) object from a degraded version of this object. The deconvolution of the degraded images is an indispensable recurring theme for the problem. Degradation comes in many forms such as aperture effects of the camera, motion blur, noise, or atmospheric turbulence, and so on. This problem has been extensively studied for its obvious practical importance as well as its theoretical interest. Various methods in spatial or frequency domain have been proposed for the purpose [1]. In order to realize the goal of realtime inspection in detail for a satellite, the quick algorithm for restoration and the realtime system corresponding to it must be employed.

Considering the fact that the remote sensing image is mainly captured by a linear CCD with the push-broom way which the image varies over time, the time-varying wavelet packets for remote sensing image restoration is proposed in the paper. In order to realize the algorithm, we presented a dual DSPs real-time parallel system. It can realize the time-varying wavelet packet image restoration algorithm with 4096*4096 images in real-time by demonstrated by our experiment in practice.

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2. METHODOLOGY

2.1 Image restoration model based on wavelet transform

Generally speaking, the observed noisy image g (i, j) consist of unknown desired image f (i, j) first degraded by convolution with a low pass filter (blurring function) h (i, j) from a linear time- invariant (LTI) system H and then corrupted by zero-mean additive white Gaussian noise (AWGN) η (i, j) with variance (see Fig. 1). It can be expressed as follows:

$$g(i,j) = h(i,j) \otimes f(i,j) + \eta(i,j) \qquad (1)$$

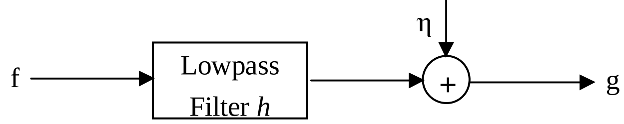


Fig.1. General degradation model.

The quickest and easiest way to restore that is by inverse filtering but it is very sensitive to additive noise especially in high frequency domain. Although the Wiener filtering is the optimal tradeoff of inverse filtering and noise smoothing, in the case when the blurring filter is singular, the Wiener filtering actually amplify the noise. The restoration based on wavelet transform (WT) [2, 3] figures prominently in a number of recent advanced deconvolution algorithms. All these methods have the same two basic steps in common:

Inversion: Compute the noisy estimate $\hat{F} = H^{-1}G$. This inversion necessarily amplifies noise components at frequencies where H is small.

Regularization by wavelet Denoising: Compute the discrete wavelet transform (DWT) of $\hat{f}$, and then threshold and invert the DWT to obtain the final image estimate $\tilde{f}$.

The diagram is shown as follows.

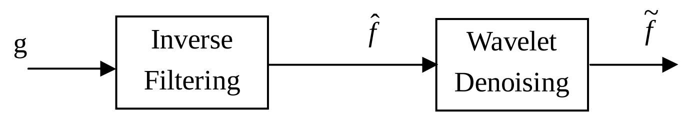


Fig.2. Wavelet restoration model.

In this paper, we followed the same steps but the method of wavelet denoising was adaptive Wiener filtering [4, 5, 6] based on minimizing Mean Square Error (MSE) rule. Adaptive Wiener filtering in the subbands of best basis based on edge detection [7] with time-varying wavelet packets for denoising is proposed in the paper.

2.2 MMSE filter based on wavelet

Let $y(i,j)$ and $\hat{x}(i,j)$ denote the noisy image and denoised image wavelet coefficients value, respectively. The minimizing MSE (MMSE) [4] estimation type of method estimate $\hat{x}(i,j)$ from $y(i,j)$ as follows:

$$\hat{x}(i,j) = \frac{\delta_x^2(i,j)}{\delta_x^2(i,j) + \delta_n^2(i,j)} y(i,j) \qquad (2)$$

where $\delta_x^2(i,j)$ and $\delta_n^2(i,j)$ are the variances of the estimated wavelet coefficient and noise, respectively. Here, it is assumed that the noise is stationary, of zero mean and variance $\delta_n^2(i,j)$, and uncorrelated with the original image.

2.3 Locally Wiener filter based on MMSE

The locally Wiener filter based on MMSE is given as follows [5]:

$$\hat{x}(i,j) = m_x(i,j) + \frac{\delta_x^2(i,j)}{\delta_x^2(i,j)+\delta_n^2(i,j)}\left(y(i,j) - m_x(i,j)\right) \tag{3}$$

where $m_x(i,j)$ is local mean in the locally small region. In (2) and (3), $m_x(i,j)$ and $\delta_x^2(i,j)$ can be estimated from the observed noisy image:

$$\hat{m}_x(i,j) = \frac{1}{(2m+1)(2n+1)}\sum_{k=i-m}^{i+m}\sum_{l=j-n}^{j+n} y(k,l) \tag{4}$$

$$\sigma_x^2(i,j) = \max\left\{\hat{\sigma}_y^2(i,j) - \sigma_n^2, 0\right\} \tag{5}$$

with

$$\hat{\sigma}_y^2(i,j) = \frac{1}{(2m+1)(2n+1)}\sum_{k=i-m}^{i+m}\sum_{l=j-n}^{j+n}\left(y(k,l) - \hat{m}_x(i,j)\right)^2 \tag{6}$$

The filter size is $(2m+1)\times(2n+1)$ fixed over the entire observed image, and is often chosen as 3×3, 5×5,7×7 in the paper.

2.4 Adaptive filter based on significant or insignificant signal

It is known that the performance of the filter of (2) and (3) is affected by the accuracy of these estimated statistics [5]. The accuracy is rather high in flat regions where brightness variation is small, but it is low in edge regions where brightness variation is large.

As the same as [6], the different filters for significant and insignificant signals are considered based on MMSE estimation. This is (7):

$$\hat{x}(i,j) = \begin{cases} (4) \quad Equation \quad if \quad y(i,j) \quad is \quad \text{significant} \\ (3) \quad Equation \quad otherwise \end{cases} \tag{7}$$

The information of low frequency ($A_J y(i,j)$) and the edge of high frequency ($\left(W_s^1 y(i,j), W_s^2 y(i,j), W_s^3 y(i,j)\right)_{1\le s\le J}$) is significant signal and the other is insignificant signal.

2.5 Edge detection

A new simple edge detection method that only need threshold is proposed as follows:

$$\text{edge (i, j)} = \begin{cases} 1 \quad if \quad sub(i,j) > \dfrac{1}{|S_{m*n}|} \sum_{sub(i,j) \in S_{m*n}} sub(i,j) + \alpha \\ 0 \qquad otherwise \end{cases} \tag{8}$$

where edge (i, j) is the edge information(1 represents edge); sub (i, j) is wavelet coefficient value in each subband of a image DWT; S_{m*n} is the subband window, and α is a plus constant. The error problem of other edge detection ways can be overcome with the new method because the method that only need threshold one by one without computing the whole element in the subbands.

2.6 Varying-time wavelet packet

To utilize the multiscale characteristics of wavelet transform more sufficiently, we developed adaptive image restoration method with varying-time wavelet packets. The method allows for the decomposition of image signal with various frequencies in the subband domain. The proposed filters in the paper explicitly incorporate both within and between subband relations of the decomposed image. The adaptive filter is used in the approach for considering local adaptation in each subband. On one hand, the result of the method is that the problem of the correlation between the images is solved, and on the other hand, it is the method that can remarkably reduce the calculating overhead and the data throughput, which is a key innovation for a real-time system.

It is difficult to find a signal-adaptive best basis in a computational attractive framework. The cost function for basis comparison here is the theoretical dimension [8] of sequences $\{x_i\}$ as follows:

$$H(x) = \exp(-\sum_i \frac{|x_i|^2}{\|x\|^2} \log(\frac{|x_i|^2}{\|x\|^2})) \tag{9}$$

where H is a Hilbert space.

Different from [7], in this paper the double tree algorithm [9] is employed to find the best basis algorithm. That is because the single tree algorithm [9] only can effectively find the best “static” frequency decomposition for the unsegmented signal taken as a whole whereas the double tree algorithm can represent an adaptive representation framework using time-varying bases. It is known that a number of signal classes in applications like speech, images and video typically exhibit time-varying characteristics that are better handled if the frequency decompositions can be made dynamic. The remote sensing images, especially which are captured by a linear CCD with the push-broom way，have the characteristics obviously. In order to match the signal’s locally varying time- or space-frequency characteristics best, the double tree algorithm is indispensable to get the adaptive wavelet packets.

3. HARDWARE REALIZATION OF RESTORATION SYSTEM

3.1 System structure

In order to realize the restoration algorithm of huge data from satellite image, we presented a dual DSPs real-time parallel system. The system is made up of double DSPs: TMS320C6416-7E3 [10], which is now the quickest one in the

DSP world. The chip works at the frequency of 720MHz and reaches 5760MIPS (Million Instructions per Second). We found that the parallel system can reach 11520MIPS, that is to say, 11.52 billion instructions per second. That is enough to real-time execute the much complicated programs of image processing.

The parallel system based on C6416 DSP has the characteristics of modular and flexible design, high scalability and maintainability. During the course of the design, the loose couple and close couple are both considered. In this paper, the ping-pong structure and the streamline structure are both designed in the system. According to the complexity of the algorithm and the requirement of the data throughput, one of the two parallel structures can be realized freely only by changing a bit in the system.

The whole system is controlled by CPLD (Complex Programmable Logic Device), which provides some controlling signals for FIFOs (First-in First-out memories), interrupt and other control signals for system written by VHDL language. The program of CPLD can be reconfigured through JTAG with the environment variation and updated to extend the function easily and flexibly. That strengthens the adaptability and flexibility of the whole system.

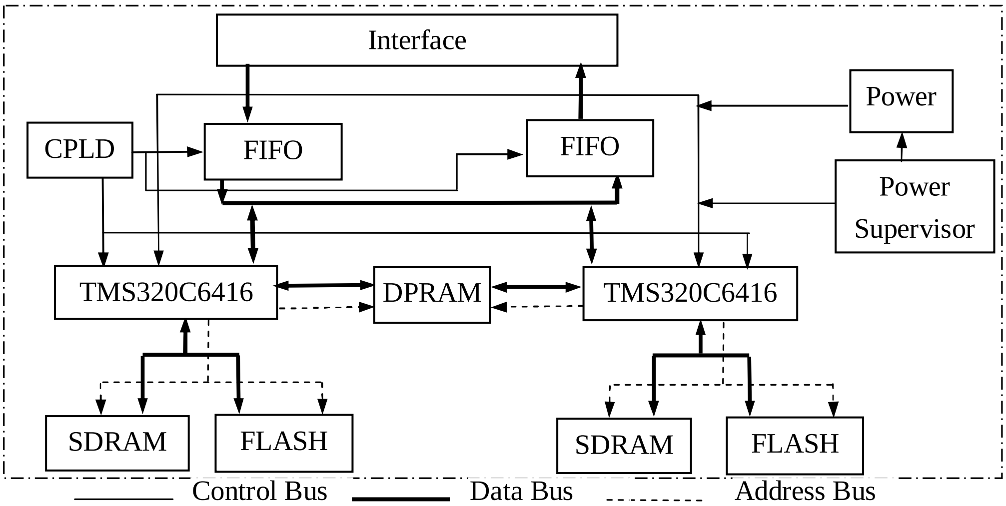


Fig.3. Real-time parallel hardware system of image restoration

3.2 System designing

As a subsystem of satellite theory system, the image restoration system was connected to other subsystems (such as capture subsystem, display subsystem and so on) by the different converters. The outputs of these different converters have high-current capability for driving balanced lines, such as twisted-pair or parallel-wire transmission lines. It is possible for the connection of the whole system, which is made up of some subsystems, by this kind of capability.

The core of the parallel system is TMS320C6416-7E3 that can execute up to eight instructions every clock cycle to achieve 5760MIPS performance at 720MHz. By the parallel designing of two DSPs, the parallel system can reach 11520MIPS, that is to say, 11.52 billion instructions per second. It can meet the computation capacity need of the restoration algorithm for remote sensing 4096*4096 image.

The C6416 has two EMIFs (External Memory Interfaces), EMIFA (64-bit) and EMIFB (16-bit), per device. We know that the EMIFs of all TMS320C6000 devices support a glueless interface to a variety of synchronous and asynchronous external devices including SBSRAM, SDRAM and SBSRAM. Besides, the C6416 EMIFs offers additional flexibility by replacing the SBSRAM mode with a programmable synchronous mode, which supports glueless interfaces: ZBT (Zero Bus Turnaround) SRAM, synchronous FIFO and SBSRAM. To resolve the problem of quantities of processing data, two 2M×32 SDRAM memories are integrated with each C6416.

In spite of the performance of core processor, an excellent system structure design is also very important. According to the high-speed image processing system, the problem of conflict between input or output unit and processing unit must be resolved well. The access of C6416 to external memory, especially to asynchronous SRAM, is much slower than to internal memory. Each access to external memory needs 4~5 DSP EMIFA (or EMIFB) clock cycles meanwhile C6416 can execute 100~150 instructions. A reasonable structure may reduce the fetching and waiting time for DSP to access external memory. Two synchronous FIFOs have been applied in this system to synchronize input (or output) images writing to (or reading from) FIFO and DSP reading from (or writing to) FIFO. FIFO provides two independent ports with separate control, and I/O pins that permit independent, synchronous access for reading or writing. The use of FIFO to store image data efficiently avoids the conflict in data bus. It reduces the quantity of isolator and the board size therefore.

It is usual for the data exchanging between two DSPs, so a DPRAM (Dual Ports RAM) was applied in this system to exchange these data. DPRAM provides two independent ports with separate control, address, and I/O pins that permit independent, asynchronous access for reading or writing to any location in memory. The use of DPRAM to store exchanging data efficiently can solve the problem of the communication of the two DSPs.

The controlling unit of the system by CPLD is in charge of generating /CE (Chip Enable), /WE (Write Enable), /RE (Read Enable) signal of the two FIFOs and other control signal such as interrupt, system controlling and bank selection. The ping-pong structure or the streamline structure in the system can be selected by CPLD.

If the power provides to C6416 surges rather large, the system will be out of control. A low ripple DC-DC regulator and a supervisor circuit are integrated into the system here to provide stable 3.3 and 1.4V. If the voltage falls lower than limited value, the supervisor circuit will reset the whole system automatically. When voltage becomes normal, system can reboot itself.

3.3 Working flow

The working flow of the parallel system for the ping-pong structure can be described as following:

When the horizontal sync signal is detected, the digitalized input data from the different converters are stored into the input FIFO controlled by CPLD. Once the counter in the CPLD counts a certain number, an interrupt signal is sent to notice DSP1 to halt the current processing to read data from the input FIFO. Then DSP1 reads the data from the input FIFO and implements restoration and stores processed data into the SDRAM of DSP1 temporarily. Meanwhile the data in the output FIFO from SDRAM of DSP2 are read to the output different converts controlled by CPLD. When CPLD counts the certain number again, another interrupt signal produced by CPLD is sent to DSP2. Then DSP2 reads the data from the input FIFO, implements restoration and stores processed data into the SDRAM of DSP2 temporarily. Meanwhile the data in the output FIFO from SDRAM of DSP1 are read to the output different converts controlled by CPLD. The process with DSP1 and DSP2 mentioned above will be run in turns all along. To settle the conflict of different signals, the whole process is strictly controlled by CPLD.

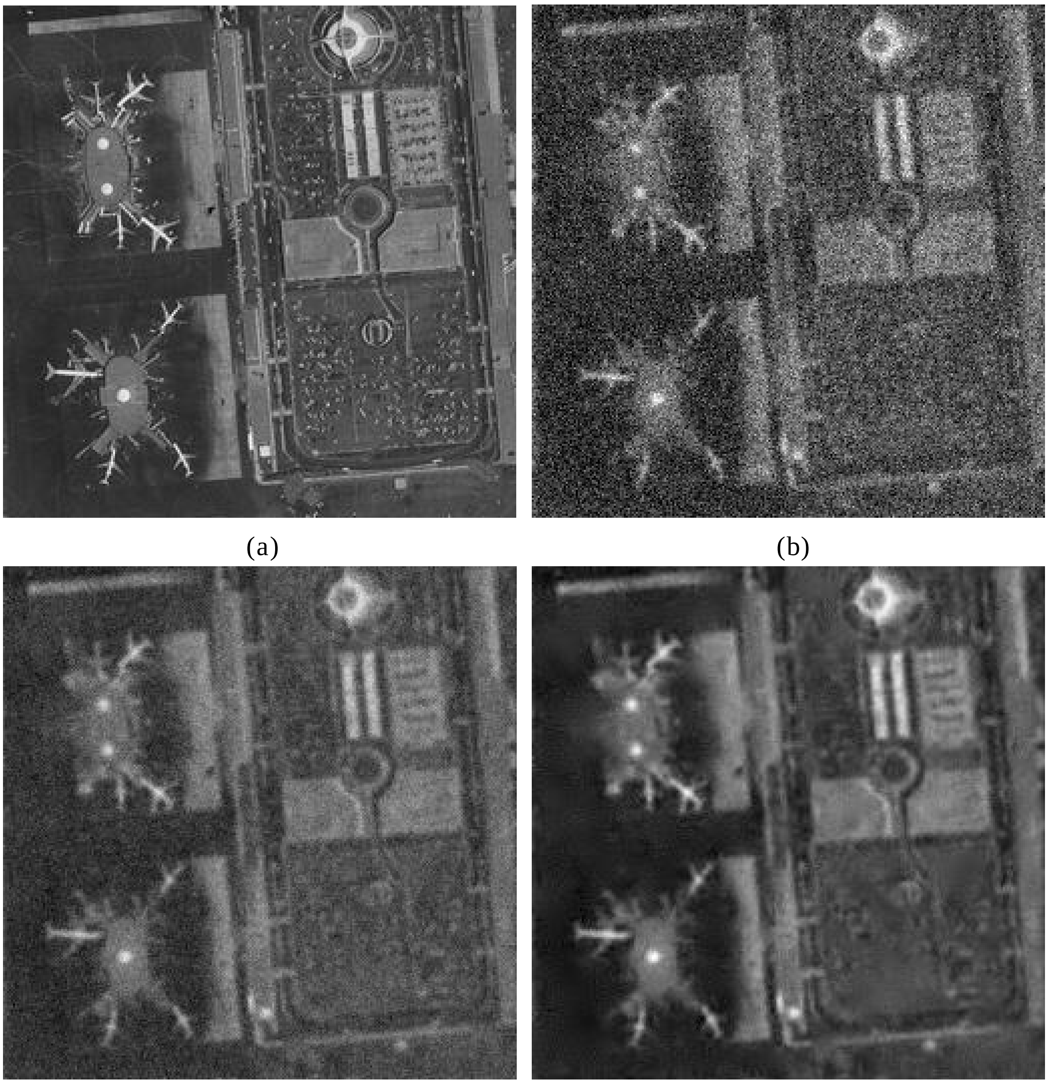
4. RESULTS

To verify the validity of the proposed method, the simulation for wavelet packet restoration is performed. In this paper, each observed image is wavelet transformed up to the third scale so that the image is decomposed into 84 subbands and the filtering is implemented in each subband of the best basis found by the double tree. The window sizes of the proposed filter used here is 3×3, 5×5,7×7 at the third, second, and first scale, respectively. The Daubechies 5 wavelet is used in the paper. The plus constant α of regularized parameter in (8) is chosen as 0.05. To evaluate the performance of the proposed method, computer simulation was performed on 512*512 Lax and Road images. The MSE and ISNR are used in the paper for evaluating the results. The MSE is defined by:

$$MSE = \frac{1}{N^2}\left\| f - \hat{f} \right\|^2 = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left[f(i,j) - \hat{f}(i,j) \right]^2 \tag{10}$$

The improved SNR (ISNR) is defined by:

$$ISNR_{\hat{f}} = 10\lg \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[f(i,j) - g(i,j) \right]^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[f(i,j) - \hat{f}(i,j) \right]^2} \tag{11}$$



(a) (b)

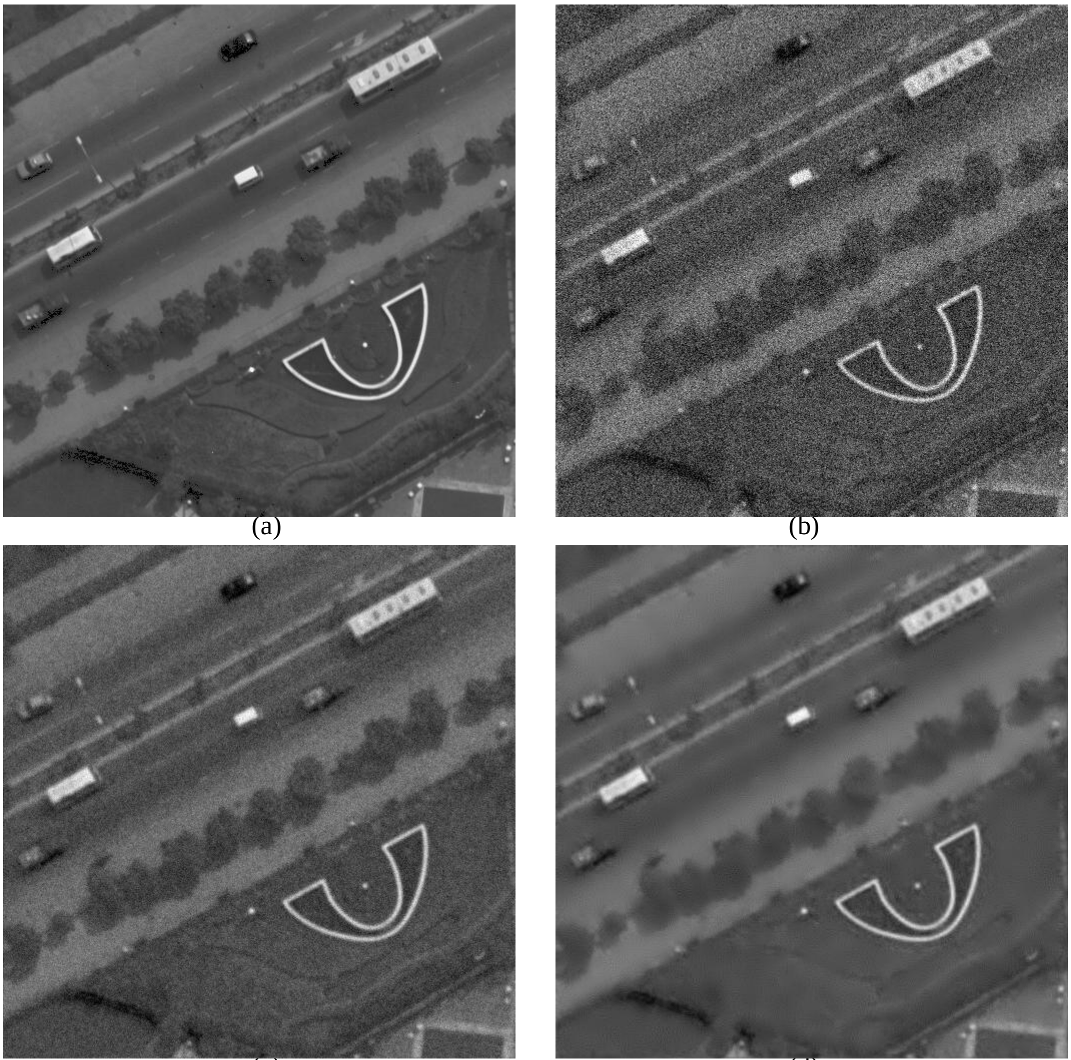
(c) (d)

Fig.4. Results of wavelet restoration for Lax image:

(a) Original; (b) blurred and noisy (input SNR = 10dB); (c) Wiener filter (WF); (d) proposed method (PM).

$$H = \frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix} \tag{12}$$

The images were corrupted by convolving wit a blurring filter H of (12) and adding AWGN with zero mean under various input SNRs. The restoration step follows the wavelet restoration model Fig.2. In Table 1, one can see that the performance improvement is accomplished. In this case, from Fig.4 and Fig.5, one can see that the image restored by the proposed method shows much better quality than that restored by Wiener filter.



(a) (b) (c) (d)

Fig.5. Results of wavelet restoration for Road image:

(a) Original; (b) blurred and noisy (input SNR = 10dB); (c) Wiener filter (WF); (d) proposed method (PM).

Table 1. Performance of the restoration according to various input SNRs for test blurred images

Noise (db)	Lax				Road			
	MSE		ISNR		MSE		ISNR	
	WF	PM	WF	PM	WF	PM	WF	PM
30	723.5	737.71	-0.90725	-0.98651	54.12	62.772	5.9079	5.2554
20	522.75	555.78	0.92211	0.66674	78.949	52.66	5.4836	7.241
15	315.09	352.3	3.9987	3.497	336.81	66.192	1.1561	8.2355
10	1113.8	474.65	0.48226	4.179	945.97	208.36	0.047202	6.6284
5	2359.2	1238.6	0.51016	3.3717	1410.3	507.4	2.6221	7.0841
0	2180.3	2534	5.2073	4.5584	2114.6	1853.5	5.6336	6.2081

5. CONCLUSION

Reviewing the fact that the remote sensing image is mainly captured by a linear CCD with the push-broom way which the image varies over time, the time-varying wavelet packets for remote sensing image restoration is proposed in the paper. On one hand, the result of the method is that the problem of the correlation between the images is solved, and on the other hand, it is the method that can remarkably reduce the calculating overhead and the data throughput, which is a key innovation for a real-time system.

The proposed approach needn't iteration and can reach the goal of quick image restoration. Experimental results, which could test the proposed method, are got the target. It is found that the proposed method shows not only great noise reduction in the processed images but significant improvement of subjective image quality over the conventional image restoration methods as well.

In order to realize the algorithm, we presented a dual DSPs real-time parallel system. The parallel system based on TMS320C6416-7E3 DSP has the characteristics of modular and flexible design, high scalability and maintainability.

It can realize the time-varying wavelet packet image restoration algorithm with 4096*4096 images in real-time by demonstrated by our experiment in practice.

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