Chin. J. Astron. Astrophys. Vol. 3 (2003), No. 6, 587–596
(*http://www.chjaa.org* or *http://chjaa.bao.ac.cn*)

Chinese Journal of
Astronomy and
Astrophysics

Wavelet Analysis of Space Solar Telescope Images

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Received 2002 December 10; accepted 2003 September 1

Abstract The scientific satellite SST (Space Solar Telescope) is an important research project strongly supported by the Chinese Academy of Sciences. Every day, SST acquires 50 GB of data (after processing) but only 10GB can be transmitted to the ground because of limited time of satellite passage and limited channel volume. Therefore, the data must be compressed before transmission. Wavelets analysis is a new technique developed over the last 10 years, with great potential of application. We start with a brief introduction to the essential principles of wavelet analysis, and then describe the main idea of embedded zerotree wavelet coding, used for compressing the SST images. The results show that this coding is adequate for the job.

Key words: stars: images — techniques: image processing — methods: wavelet analysis

1 INTRODUCTION

The scientific satellite SST (Space Solar Telescope) is a research project strongly supported by the Chinese Academy of Sciences (Ai 1996, 1998). This high-resolution telescope will be sent into the outer atmosphere to collect continuous data from the sun over a broad optical spectrum, so participating in the great advance in solar physics research and the supply of important database for outer space weather broadcast and research in the motion of celestial bodies. SST carries a total of five large scale receivers, or, 15 broad coverage imaging CCDs and several hundreds of channels of the energy spectrum and frequency spectrum. It acquires 1730 GB of raw data every day, which are processed down to 50 GB. However, only 10 GB of the data may be transmitted to the ground. This is because of limited satellite passage time and channel volume. So, the image data must be compressed to less than 1/5 in order that all the data are transmitted. The compressing scheme used in SST is a real time process, with several pre-processing buffer units before the compressing units, the compressed results are ultimately stored in a storage with a huge capacity, to wait for transmission to the ground. Allowing for a certain channel transmission margin, the requirement set by the SST is that, after the image data are compressed to 1/5 of the original size, the signal to noise ratio must not fall below 28 dB, while the quality of the compressed images should satisfy intuitive astronomical demands. Thus, in-orbit, high compressing-ratio compression of images figures as an important component of SST's real time processing of scientific data.

At present, astronomical science satellites in orbit are of two kinds. Most of them target at fixed stars at large distances, e.g., *Hubble* Space Telescope. Because of the weakness of starlight, image integration time may last a few hours or even a few tens of hours, the storage and output of data are not large, and the images need not be compressed in orbit. The other kind of astronomical science satellites aims at observation of the sun and planets, e.g., *Solar B*, *Trace*. The instruments on board are not so various nor so complex as the SST, their CCD array face is also smaller, and they use many ground stations or intermediary satellites for data transmission, so, the transmission of data is not such a problem for them as for the SST. The *Hubble* Space Telescope also does not need compress the data before transmitting to the ground.

Wavelet analysis is newly, rapidly developed technique in the last 10 years, with wide scope for application. It is a way of analyzing the time scales of signals. It has the characteristics of multi-resolution analysis and the capability of expressing local features of signal in both the time and frequency domains. It is a local analysis, with windows of fixed sizes and varying shapes. That is, it has a much higher frequency resolution and lower time resolution in lower frequency bands, and a much higher time resolution and lower frequency resolution in higher frequency bands. Wavelet analysis has been called a microscope of signal analyzing. Because of multi-resolution ability of wavelet analysis, signals and images can be decomposed at different scales, and compressed in the wavelet domain. Then the original images are recovered through the inverse transform. Wavelet analysis is superior to conventional DCT (Discrete Cosine Transform) in the application of images processing and compression, as has been proven in many practical cases. Wavelet analysis differs from Fourier Transform in that different wavelet families have different compressing effects when applied to the same image. The same wavelet family also has a bigger contrast to different image processing. Therefore, the selection of a good wavelet base is extremely important to the entire compression scheme. On one hand, a good base can ensure the realization of the desired compression radio; on the other hand, it ensures that the compressed images will reach both the subjective and objective quality demands of the SST. In this article, after a brief introduction to the essential principles of wavelet analysis, we present a brief chart of embedded zerotree wavelet code. The results of the compression of SST images are discussed in detail based on the wavelets Bior9.7, Sym8, Db6 (Cohen et al. 1992; Daubechies 1988). Our conclusion is given in the end of the paper.

2 ESSENTIAL THEORY AND METHOD OF WAVELET ANALYSIS

As we know, the wavelet function originated from MRA (Multi-Resolution Analysis), the main idea of which is that a function $f(t)$ in L^2 is expressed as a series of gradually approaching expressions, any one of which is smoothed $f(t)$ at a given resolution. MRA, also called MSA (Multi-Scales Analysis), is the theory founded on the basis of function space concepts, the ideas of MRA originated from engineering. Its creator S. Mallat set up the theory when researching on image processing. At that time, people worked on images using generic means, i.e. decomposing images on different scales, and comparing the results to gain useful information. MRA plays a key role in orthogonal wavelet transform theory. Here, only established results are given, for more details refer to the References (Antonini et al. 1992; Li 2001; Liu 1992; Mallat 1989).

2.1 Definition of Dyadic Wavelet

Suppose $\psi(t)$ is a function in L^2, satisfying the condition

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0\,, \tag{1}$$

and define

$$\psi_s(t) = \frac{1}{s}\psi\left(\frac{t}{s} - k\right)\,, \tag{2}$$

where, s called the scale parameter, k called the position parameter. For $f(t) \subset L^2$, using convolution, s and k are defined below

$$w_s f(t) = (f * \psi_s)(t)\,. \tag{3}$$

The scale parameter s depicts the size and rule of signal characteristics, and must be discrete in real applications. Generally, s is simply changed as dyadic serials $\{2^j|_{j\in z}\}$, i.e.

$$w_{2^j} f(t) = (f * \psi_{2^j})(t)\,. \tag{4}$$

Equation (4) is the discrete dyadic wavelet transform. In the same way, we also have the discrete forms of $\phi_{s,k}(t)$, i.e.

$$\phi_{2^j}(t) = \frac{1}{2^j}\phi\left(\frac{t}{2^j}\right)\,, \tag{5}$$

and define Eq.(6) as MRA approach

$$s_{2^j} f(t) = \phi_{2^j} * f(t)\,. \tag{6}$$

Suppose that the least scale is 1 and the greatest scale is 2^J, then, $s_1 f(t)$ and $s_2^J f(t)$ are MRA approaches on scales 1 and 2^J, $w_2^j f(t)$ $(j \in 1, 2, \ldots, J)$ is called wavelet decomposition based on scales $1, 2, \ldots, J$.

It can be proved that (Liu 1992)

$$\|s_1 f(t)\| = \sum_{j=1}^{J} \|w_{2^j} f(t)\|^2 + \|s_{2^J} f(t)\|^2\,. \tag{7}$$

Equation (7) shows that the high frequency portion of $s_1 f(t)$ can be recovered by $w_2^j f(t)_{1\le j\le J}$, so

$$s_{2^J} f(t)\,, w_{2^j} f(t)_{1\le j\le J}\,, \tag{8}$$

is called the finite scale wavelet transform of $s_1 f(t)$.

In real applications, generally, most of the signals we obtained are discrete digital signals. It is proven theoretically that any energy-limited discrete signal can be represented as uniform samples through a smoothened function on scale 1, i.e., the MRA approach. Therefore, any energy-limited discrete signals can be decomposed and reconstructed by discrete wavelet transform.

2.2 Mallat Algorithm

From experience gained from images decomposition and reconstruction cascade algorithm, Mallat put forward the algorithm in the MRA theory now bearing his name. This algorithm plays a role in wavelet transform as important as does FFT (Fast Fourier Transform) in Fourier Transform.

It is proved mathematically that

$$f(t) = A_j(t) = A_{j+1}f(t) + D_{j+1}f(t) \,, \tag{9}$$

and among them, we have

$$A_{j+1}f(t) = \sum_{m=-\infty}^{+\infty} C_{j+1,m}\psi_{j+1,m} \,, \tag{10}$$

$$D_{j+1}f(t) = \sum_{m=-\infty}^{+\infty} D_{j+1,m}\phi_{j+1,m} \,, \tag{11}$$

and

$$C_{j+1,m} = \sum_{k=-\infty}^{+\infty} h_{k-2m}C_{j,k} \,, \tag{12}$$

$$D_{j+1,m} = \sum_{k=-\infty}^{+\infty} g_{k-2m}D_{j,k} \,. \tag{13}$$

The above can be written in a compact form as follows:

$$\begin{cases} C_{j+1} = HC_j \\ D_{j+1} = GD_j \end{cases} \qquad (j = 1, 2, \ldots J) \,. \tag{14}$$

Expression (14) is the Mallat pyramid scheme. We call C_j, D_j discrete approximations and discrete details respectively. After a proper mathematical transformation of Eq. (9), Mallat reconstruction scheme becomes

$$C_j = H^*C_{j+1} + G^*D_{j+1} \qquad j = J, J-1, \ldots \,, \tag{15}$$

where H^* and G^* are the complex conjugates of H and G.

2.3 Two-Dimensional Wavelet For Image Analysis

There exist various extensions of the one-dimensional wavelet transform to two-dimensional and indeed multi-dimensional wavelet, but separable two-dimensional wavelets are simple and effective in common use. Same as in the construction of one-dimensional wavelet, the scale function $\phi(x, y)$ is defined as

$$\phi(x, y) = \phi(x)\phi(y) \,, \tag{16}$$

where $\phi(x)$, $\phi(y)$ are the one-dimensional scale functions. Suppose $\psi(x)$ denotes the wavelet function related to the one-dimensional scale function, then three two-dimensional wavelets are defined by

$$\psi^H(x, y) = \phi(x)\psi(y) \,,$$

$$\psi^V(x, y) = \psi(x)\phi(y) \,,$$

$$\psi^D(x,y) = \psi(x)\psi(y)\,. \tag{17}$$

Figure 1 shows the two-dimensional wavelet transform of an image. The two-dimensional MRA decomposition is completed in two steps. First, using $\phi(x)$ and $\psi(x)$ in the x direction, $f(x,y)$ (an image) is decomposed into two parts, a smooth approximation and a detail. Next, the two parts are analyzed in the same way using $\phi(y)$ and $\psi(y)$ in the y direction. As a result, four channel outputs are produced, one channel is $A_1 f(x,y)$, the level one smooth approximation of $f(x,y)$, through $\phi(x)\phi(y)$ processing, the other three channels are $D_1^{(H)} f(x,y)$, $D_1^{(V)} f(x,y)$ and $D_1^{(D)} f(x,y)$, the details of the image. Grade two and level three results are obtained after decomposing $A_1 f(x,y)$ progressively. The algorithm of two-dimensional wavelet decomposition and reconstruction is the same as that for one-dimensional wavelet. Mallat pyramid scheme is also used in this case. Figure 2 is a sketch map of a three-level two-dimensional wavelet transform.

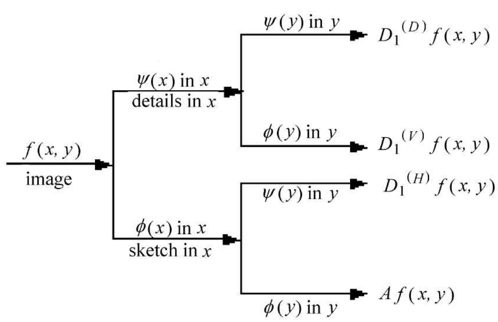

Fig. 1 Image decomposition with separable two-dimensional wavelets.

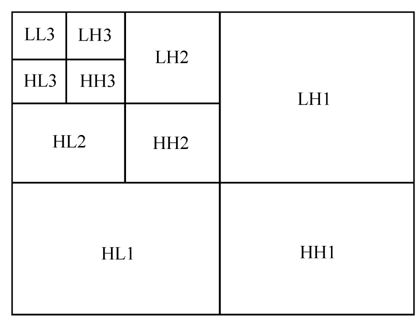

Fig. 2 Sketch map of three-level two-dimensional wavelet transform.

3 THE PROCESS AND PRINCIPLE OF ZEROTREES WAVELET IMAGE COMPRESSION

3.1 The Process of Image Compression

The process of image compression based on wavelet transform coding is shown in Fig. 3. The purpose of the wavelet transform is to decorrelate the image, the process is loss-less and reversible when calculating errors are ignored. A series of wavelet coefficients is formed in the transform domain after the image decorrelation, which is quantized to integers to a code bit stream to be transmitted down. The quantization is not lossless nor reversible, and is mainly responsible for image distortion. Figure 4 shows the process of decoding and recovering image, it is the reverse of Fig. 3.

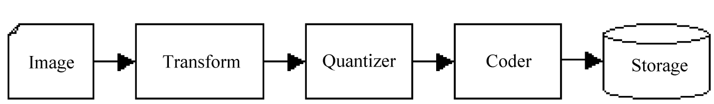

Fig. 3 Sketch of image wavelet transform and coding.

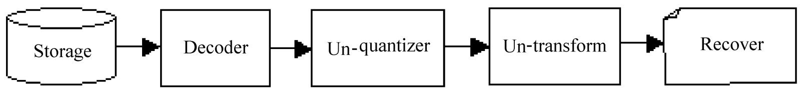

Fig. 4 Sketch of image recovery and decoding.

3.2 The Principle of Zerotree Wavelet Compression

Quantization is the key to image compression. The embedded zerotree wavelet compression scheme with high compression efficiency is used to quantize post-transformation wavelet coefficients. Some highlights of the method now follow.

The embedded zerotree wavelet compression scheme was proposed by Shapiro in 1993 (Shapiro 1993), the main idea of which is the investigation of self-similarity of the wavelet transforms of the image at different scales. In the orthogonal tree data structure, every node (except the exit node) has four offsprings, and a zerotree root implies that all coefficients corresponding to the nodes of the tree are insignificant comparing to the specified threshold, and only the zerotree root rather than whole tree, needs to be coded, and so compressing the image on the given level. The zerotree wavelet compression scheme is based on the following presumption, namely, if the wavelet coefficients are insignificant on a coarse scale (e.g. HH3 in Fig. 2), then it is highly likely that the wavelet coefficients in the same space position and direction (e.g. HH2, HH1 in Fig. 2) are insignificant at finer scales. This Shapiro hypothesis is confirmed by a great deal of statistical data of wavelet coefficients on images, so the Shapiro method is widely used in image compression processing and other domains.

In order to have a higher compressing radio, the quantization should result in more of the wavelet coefficients being zero. Quantization begins from the lowest frequency subband LL3, the order is LL3- LH3-HL3- HH3- LH2-HL2- HH2- LH1-HL1- HH1. The scan begins by taking the half-integer of the greatest wavelet coefficient as threshold, and the wavelet coefficients with absolute value greater than the threshold are taken to be significant, denoting positive and negative significant values with POS and NEG, and isolated zero point and zerotree root with IZ and ZTR respectively. After the first scanning, we have the threshold and repeat the process until the desired compression ratio or bit budget is reached. The decoding process is accomplished according to the order of subband coding, the details are given in the references (Said 1996; Shapiro 1993).

4 WAVELET ZEROTREE COMPRESSION RESULTS OF SST IMAGES

4.1 The Characteristics of Embedded Zerotree Wavelet Image Coding

Embedded coding is similar in spirit to binary finite-precision representations of real numbers. All real numbers can be represented by a string of binary digits. As each digit is added to the right of binary figure string, more precision is added. The binary coded stream can realize progressive transmission using multi-threshold embedded zerotree wavelet coding, the coding rate and distortion can be controlled accurately. According to the order of importance of the bit plane, the most important bit plane is coded first, and the coding can end at any time when the bit budget or compression ratio is reached. When transmitted, the most important bit plane is transmitted first, and the least important, last. The decoding can be stopped on occasion depending on the decoded image quality. The characteristics described above of embedded coding are very suitable to the real time transmission of images. When receiving the images, a rough sketch of image is received first, then, we decide whether or not to continue receiving, for it is useful to save the channel resource. SST images are transmitted to surface receiver stations from remote space and the channel resource is valuable, while embedded zerotree wavelet coding of the images is also useful to SST image processing.

4.2 The Choice of Wavelet Basis

As we know, different wavelet have different performances for the same image compression, and there is no universally best wavelet basis for all the different kinds of image processing; even if there is such a wavelet, it will be of no use in practice and it will not have good characteristics. The performance of wavelet compression of images depends principally on the inherent statistical information of the image. When our aim is to compress SST, the selection of a right wavelet basis is extremely important, in order to acquire compressed images that satisfy the subjective and objective quality demands.

There are two well-known wavelet filter families used in wavelet-based image coders, i.e. orthogonal and biorthogonal wavelets. Orthogonal guarantees that images transformed can be fully recovered through the inverse transformation, and compact support guarantees realizability of coding, the smaller support interval (i.e. the less wavelet coefficients), the less compute time. However, the length of the support interval is closely related to smoothness and regularity of wavelet, and which inversely affects coding features. The main attraction of biorthogonal wavelet is the linear phase of FIR (Finite Impulse Response), there is no need to make phase compensate in pyramid multi-decomposition structure. To sum up, in the selection of wavelet we need to trade off among orthogonal, symmetric, support interval, smoothness and regularity. In this article, based on the results of SST images compression using Matlab Program, compact support biorthogonal Bior9.7, orthogonal Db6 and Sym8 wavelet with smoothness 4, 6, 8 respectively, are chosen in a C program for SST images compression, and the compressed images proved to be satisfactory, satisfying the subjective and objective quality demands of the SST.

Table 1 Compressed Sunspot Results during a Solar Burst (dB)

CR	5	10	20	30	Notes
Bior9.7	39.23	34.71	26.62	19.70	SNR
	45.95	41.42	33.33	26.42	PSNR
Sym8	39.48	31.68	23.54	19.19	SNR
	46.19	38.39	30.25	26.61	PSNR
Db6	39.33	31.33	26.46	19.60	SNR
	46.05	38.05	33.18	26.31	PSNR

Table 2 Compressed Flare Results during the Quiet Sun (dB)

CR	5	10	20	30	Notes
Bior9.7	36.60	33.99	31.67	26.12	SNR
	44.34	41.72	39.41	33.86	PSNR
Sym8	36.72	34.07	28.45	24.79	SNR
	44.46	41.80	36.19	32.52	PSNR
Db6	36.70	34.04	28.10	24.09	SNR
	44.44	41.77	35.84	31.82	PSNR

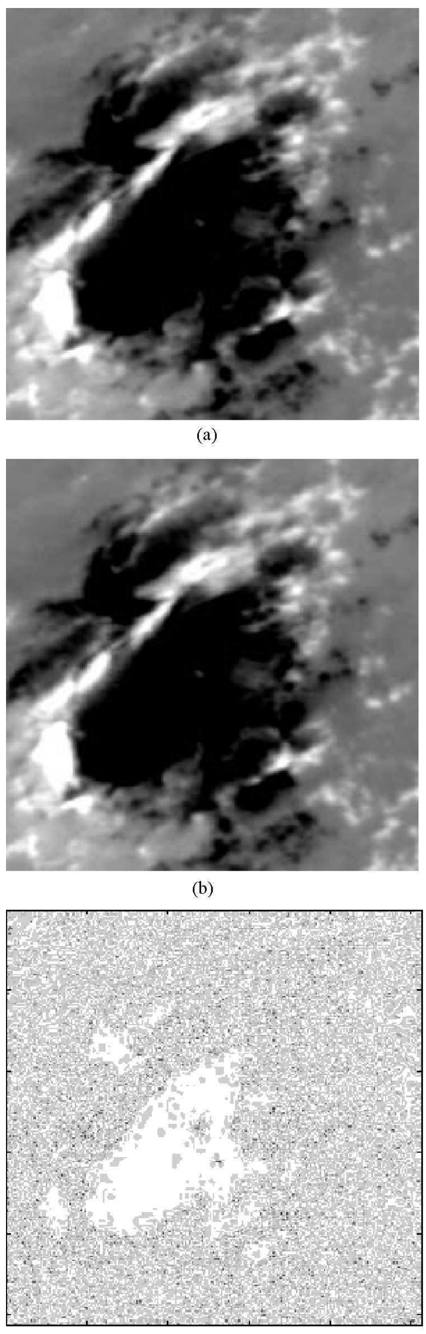

Fig. 5 Original and compressed images of sunspot compared. (a) Original sunspot image; (b) Bior9.7 compressed image; (c) Magnified 36 times error image.

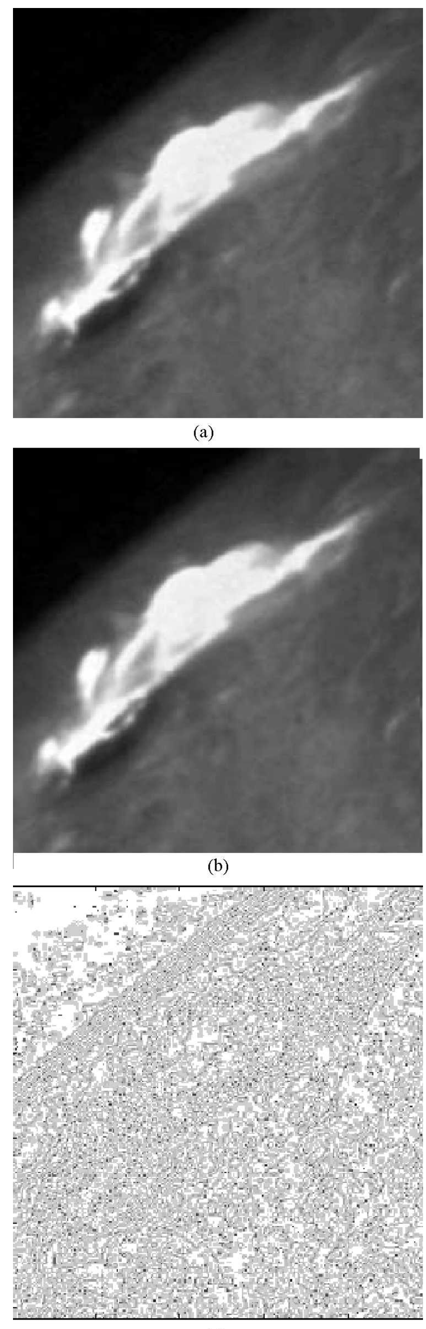

Fig. 6 Original and compressed images of flare compared. (a) Original flare image; (b) Bior9.7 compressed image; (c) Magnified 36 times error image

4.3 Results of Compressed SST Images

The SST images include images of sunspots, flares, solar activity and bursts. In this article the zerotree wavelet compressing scheme is applied to 20 SST images of various kinds (all the images originate from the Huairou Station, National Astronomical Observatories), with compression ratios 5, 10, 20, 30, and a four-level decomposition, with the wavelets Bior9.7, Db6 and Sym8 wavelets separately. Partial results are shown in Table 1 and Table 2. The Tables list the compressed signal to noise ratio (SNR) and peak signal to noise ratio (PSNR), in units of dB. The results in the Tables show that, whether it is a flare or a sunspot, when the CR (compression ratio) is below 10, the compressed effects of Bior9.7, Db6, Sym8 are essentially the same and all satisfy the requirement that the SNR be no lower than 28dB after a CR of 5. For the sunspot during the quiet sun, the compressed results also satisfy the 28dB requirement, when the CR is 20. On the other hand, when CR is 20 or 30 times, the SNR and PSNR of Bior9.7 wavelet are 3dB higher than those of Sym8 and Db6 wavelets, and this feature is even more obvious for the flare during the quiet sun.

Figures 5 and 6 show the original images (a), and 5 times compressed images (b) and error images (c) of the sunspot during the solar burst (see Table 1) and the flare during quiet sun (Table 2 results), using Bior9.7. The error images are magnified 36 times and after reverse color processing. Comparing the original and compressed images, the SNR of the compressed images satisfies the 28dB criterion, and it is difficult to distinguish between the original and compressed images by the naked eye, thus satisfying the subjective quality demand.

The analysis of the processed results of about 20 SST images makes it clear that the three wavelets, Bior9.7, Sym8, Db6, give near equal performances with small differences in SNR and PSNR, when the CR is not large. When CR exceeds 20 Bior9.7 performs better than Sym8 and Db6 wavelet. When the CR is 5, most of the images have SNRs no lower than 30 dB, so satisfying the pre-set criterion.

5 CONCLUSIONS

The Sun is an important object of astrophysics research. Investigation of solar activity is very important for preventing accidents in air traffic, radio communication, power supply and petroleum transportation, so avoiding disasters brought by climate change and earthquake. However, a huge amount of SST images must be compressed, before being transmitted to the ground. The investigations in this article indicate that zerotree wavelet compression coding scheme is feasible for compressing SST images using the wavelets Bior9.7, Sym8 and Db6, and the compressed images meet the subjective and objective demands of quality of astronomical images.

Acknowledgements The authors would like to thank Prof. W. Li of National Astronomical Observatories, Chinese Academy of Science, for supplying the original solar images, and Prof. H. J. Guo of Beijing University of Chemical Technology for careful revision of the manuscript. This project is partly supported by the National 863 Foundation under grant 863-2.5.1.25.

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