Hindawi Publishing Corporation
Advances in OptoElectronics
Volume 2015, Article ID 496863, 5 pages
http://dx.doi.org/10.1155/2015/496863

Research Article

Block-Based Compressed Sensing for Neutron Radiation Image Using WDFB

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Received 13 December 2014; Accepted 23 March 2015

Academic Editor: Michele Norgia

An ideal compression method for neutron radiation image should have high compression ratio while keeping more details of the original image. Compressed sensing (CS), which can break through the restrictions of sampling theorem, is likely to offer an efficient compression scheme for the neutron radiation image. Combining wavelet transform with directional filter banks, a novel nonredundant multiscale geometry analysis transform named Wavelet Directional Filter Banks (WDFB) is constructed and applied to represent neutron radiation image sparsely. Then, the block-based CS technique is introduced and a high performance CS scheme for neutron radiation image is proposed. By performing two-step iterative shrinkage algorithm the problem of L_1 norm minimization is solved to reconstruct neutron radiation image from random measurements. The experiment results demonstrate that the scheme not only improves the quality of reconstructed image obviously but also retains more details of original image.

1. Introduction

Digital neutron radiography, one type of nondestructive testing technology, is a newly developing high-technology which is the combination of a set of technologies such as nuclear science, optoelectromechanical integration, and digital image processing [1]. With the development of digital neutron imaging system, the dynamic range of neutron radiation image is improved [2]; meanwhile the amount of image data is increased rapidly. The huge amount of data occupies plenty of the storage space and network resources and sometimes even becomes the bottleneck of the whole system performance improvement. For the traditional image compression methods are hard to preserve the details which are the most valuable part of the neutron radiation images at high compression ratio, how to find a rational method to reduce the amount of data of neutron radiation image has become an increasingly urgent issue. In recent years, a new theory of compressed sensing (CS) has been put forward [3, 4], and it points out that for the "sparse" signal (or the signal's transformed coefficients are "sparse" in a specific transform domain), using a random measurement matrix, the original signal is projected onto a low dimensional space to get a small part of the random measurements, and by solving an optimization problem the original signal can be reconstructed from this part of the measurements. Because the neutron radiation image meets the sparsity condition, by using the rational designed measurement matrix, the original image can be reconstructed from small projection measurements. With the help of this scheme, the sampling rate of neutron imaging system and the amount of neutron radiation image may be reduced effectively. In general, in order to reconstruct the ideal image from the random measurements, three issues should be concerned including sparse representation, measurement matrix, and reconstruction algorithm. Combining wavelet transform with directional filter banks [5, 6], a novel nonredundant multiscale geometry analysis transform named Wavelet Directional Filter Banks (WDFB) is constructed and applied to represent neutron radiation image sparsely. In order to ensure that the linear projection of neutron radiation image can keep the original information and reduce the time and space complexity of sparse measurement, we introduce block-based compressed sensing (BCS) technology [4] by using the blocked measurement matrix which satisfies restricted isometry property (RIP) to perform random measurement. Finally, the original neutron radiation image was reconstructed from the measurement by solving the problem of L_1 norm minimization based on two-step iterative shrinkage reconstruction algorithm [7, 8]. The proposed scheme is applied to the neutron radiation image and compared with

the traditional method in terms of reconstruction speed, visual effect, and the objective evaluation of reconstructed image.

2. Wavelet Directional Filter Banks (WDFB)

We know that the parts of dramatic change in the image, such as edge and contour, are the important local characteristics which often contain more information than other parts. In order to represent such directional features of neutron radiation image sparsely, we use direction filter bank (DFB) to implement multidirection decomposition to express the high dimensional singularity of image effectively. Considering that DFB can not depict image in multiresolution manner and its poor performance to represent the low frequency component of image, we use wavelet decomposition combined with directional filter banks to construct a nonredundant multiscale geometric analysis transform, and we call this transform Wavelet Directional Filter Banks (WDFB).

By using WDFB, multiscale analysis is performed via wavelet transform to capture point singularity of the image, followed by DFB to synthesize the singular points in the same direction into a coefficient. In a word, WDFB use the basic structure like contour segment to approximate the original image and the support interval of the basis function has an elongated structure with the change of directions and scales. Compared with wavelet analysis, WDFB can represent the image more sparsely. Specifically, the image is decomposed into an approximation subband LL_J and several detail subbands LH_j, HL_j, and HH_j $(1 \le j \le J)$ after J level wavelet decomposition; then, WDFB carries out DFB to the detail subbands of wavelet decomposition to obtain the direction information of image. In order to meet the anisotropy scaling relation, in the realization of DFB decomposition, the direction numbers were decreased in dyadic manner from fine to coarse scale. That is to say, if the direction numbers of the finest scale are 2^L, then the numbers of its adjacent coarser scale will be 2^{L-1}, and so on until the coarsest scale. In practical applications, the decomposition levels of wavelet and the maximum direction numbers of DFB are determined by the characteristics of actual image and the specific tasks.

3. Block-Based Compressed Sensing

In recent years, CS technology where theoretical frameworks were established by Donoho, Candes, and so forth has been developed quickly and attracted the attention of scholars. Suppose that the signal $X \in R^N$ with length N can be represented sparsely by the orthogonal basis or tight frame, that is, $C = \boldsymbol{\psi}^T X$, that is to say, there are only K nonzero coefficients in $\boldsymbol{\psi}$ domain ($K \ll N$), we call X a sparse signal in $\boldsymbol{\psi}$ domain (in this paper, $C = \boldsymbol{\psi}^T X$ refers to performing WDFB transform for X). In that case, an $M \times N$ measurement matrix $\boldsymbol{\Phi}$ can be constructed and the linear measurements $Y \in R^M$ can be obtained by

$$Y = \boldsymbol{\Phi} X = \boldsymbol{\Phi}\boldsymbol{\psi} C. \tag{1}$$

Then, the original signal can be reconstructed perfectly from measurements Y by solving the optimization problem based on the known $\boldsymbol{\Phi}$:

$$\min \|C\|_{L_0} \quad \text{subject to } Y = \boldsymbol{\Phi}\boldsymbol{\psi} C, \tag{2}$$

where L_0 norm counts the nonzero elements in the corresponding vector. Considering that the traditional CS is not suitable for sensing natural image in real-time mode for the sampling process requiring accessing the entire target at once and the reconstruction algorithms are generally very expensive, in [2], a block-based CS (BCS) for natural images was proposed. Motivated by the great success of block DCT coding systems, in BCS scheme, the original image is divided into small blocks and each block is sampled independently using the same measurement matrix.

BCS can reduce the size of compressed sensing measurement matrix significantly; moreover, the computational complexity of the reconstruction algorithm can be greatly reduced. Consider an original image X with $N = I_r \times I_c$ pixels, where I_r and I_c represent the rows and columns of image, respectively; we divided the image into small blocks with size of $B \times B$. Let X_j represent the vectorized signal of the jth block through raster scanning. Then, design an orthonormalized i.i.d. Gaussian matrix $\boldsymbol{\Phi}_B$ with size of $M_B \times B^2$ as the measurement matrix for each subblock. According to the traditional CS theory, the jth block X_j can be reconstructed from random measurements $Y_j = \boldsymbol{\Phi}_B X_j$. Finally, the original image X can be feasibly restored by integrating X_j accordingly. Obviously, if the measurement rate α is set as M/N, then $M_B = \lfloor M * B^2/N \rfloor$. For there is a trade-off in the selection of block size B, small B requires less memory in storage and faster implementation but causes mosaic in the reconstructed image, while large B offers better reconstruction performance but causes high computational and storage complexity. From empirical studies, we set block size $B = 64$ in this paper.

4. Neutron Radiation Image Reconstruction Using Two-Step Iterative Shrinkage/Threshold

How to reconstruct the original signal from linear measurements is the key to the application of CS technique. The L_0 norm optimization like (2) is both numerically unstable and nondeterministic polynomial (NP) complete problem, and it can hardly be solved in polynomial time so several alternative solution procedures have been proposed [9]. Perhaps the most prominent of these is basis pursuit (BP) which applies a convex relaxation to the L_0 problem resulting in an L_1 optimization. Although BP can be implemented effectively with linear programming, its computational complexity is often high. Other variant algorithms include conjugate gradient (CG), matching pursuit (MP), and orthogonal matching pursuit (OMP). Unfortunately, such algorithms reduce computational complexity at the cost of lower reconstruction quality.

In Daubechies et al.'s [7], L_1 optimization can be solved by iterative shrinkage/threshold (IST) algorithm. Bioucas-Dias

and Figueiredo [8] further develop this algorithm and propose a two-step iterative shrinkage/threshold (TwIST) algorithm in order to improve the convergence speed of IST. Unlike IST, in the iteration of TwIST, the new estimate depends on the two previous estimates so that the optimized results can be obtained more quickly. In this paper, we use TwIST to realize BCS reconstruction for the neutron radiation image. The following is the description of the proposed scheme in detail.

Step 1. The original neutron radiation image is divided into small blocks with size $B\times B$. X_j represent the vectorized signal of the jth block through raster scanning and then performing random measurement $Y_j = \mathbf{\Phi}_B X_j$ using the measurement matrix $\mathbf{\Phi}_B$.

Step 2. Estimating the initial reconstruction subblock $X_j^{(0)} = \mathbf{\Phi}_B^T Y_j$, set iteration counter $k = 0$.

Step 3. In order to reduce blocking effect, Wiener-filtering was carried out to the reconstructed image which was integrated by each subblock and then calculating the objective function $f(X_j^{(k)})$ corresponds to $X_j^{(k)}$ as

$$f\left(X_j^{(k)}\right) = \frac{1}{2}\left\|Y_j - \mathbf{\Phi}_B X_j^{(k)}\right\|_2^2 + \lambda\left\|\boldsymbol{\psi}^T X_j^{(k)}\right\|_{L_1}, \tag{3}$$

where $\boldsymbol{\psi}^T$ denotes WDFB transform, the parameter λ can be regarded as a regularization term, and tuning this parameter can make balance between two parts of the objective function.

Step 4. Thresholding process $X_j^{(k+1)} = S_T(X_j^{(k)})$, where the threshold function is

$$\begin{aligned} &S_T\left(X_j\right) \\ &\quad = \boldsymbol{\psi}\left\{\text{threshold}\left[\boldsymbol{\psi}^T\left(X_j + \frac{\mathbf{\Phi}_B^T\left(Y_j - \mathbf{\Phi}_B X_j\right)}{s}\right)\right]\right\}, \end{aligned} \tag{4}$$

where threshold$(\cdot)$ is hard thresholding function, to set a proper threshold $T^{(k)}$, we imply the universal threshold method $\sigma^{(k)}\sqrt{2\log N}$, and N is the number of the transform coefficients, and $\sigma^{(k)}$ is estimated using a robust median estimator. s is the iteration step and set its initial value equal to 1; then, $f(X_j^{(k+1)})$ is calculated using (3); if $f(X_j^{(k+1)}) > f(X_j^{(k)})$ set $s = 2 * s$ to recalculate $f(X_j^{(k+1)})$; otherwise continue to the next step.

Step 5. Updating the iteration counter, $k = k + 1$, and then using two previous estimates to update the current value,

$$X_j^{(k)} = (1-\alpha)\, X_j^{(k-2)} + (\alpha - \beta)\, X_j^{(k-1)} + \beta S_T\left(X_j^{(k-1)}\right), \tag{5}$$

where the parameters α and β determine the speed of convergence given by [8]

$$\begin{aligned} \alpha &= p^2 + 1, \\ \beta &= \frac{2\alpha}{1 + 10^{-4}}, \\ p &= \frac{1 - 10^{-2}}{1 + 10^{-2}}. \end{aligned} \tag{6}$$

Calculating the objective function $f(X_j^{(k)})$, if $f(X_j^{(k)}) > f(X_j^{(k-1)})$ then return to Step 3; otherwise continue to the next step.

Step 6. The iteration will be terminated if $E(X_j^{(k)}, X_j^{(k-1)}) < \delta$, where δ is the preset small number; else return to Step 5. $E(\cdot)$ is defined as

$$E\left(X_j^{(k)}, X_j^{(k-1)}\right) = \frac{\left|f\left(X_j^{(k)}\right) - f\left(X_j^{(k-1)}\right)\right|}{f\left(X_j^{(k-1)}\right)}. \tag{7}$$

Then the final reconstruction image can be obtained via integrating $X_j^{(k)}$ accordingly.

5. Experimental Results and Analysis

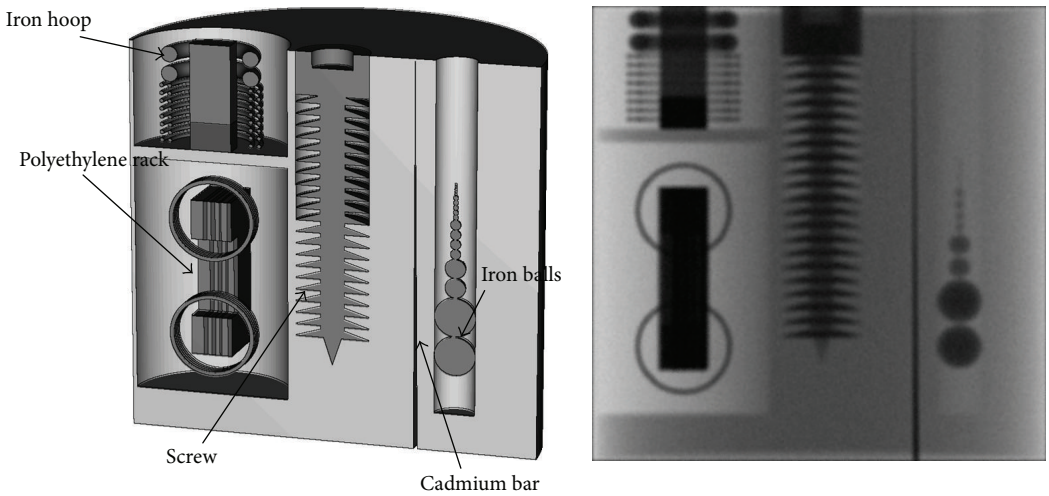
In order to verify the effectiveness of the proposed scheme, the compressed sensing experiments were performed on the neutron radiation image of a test specimen. The digital neutron imaging system was carried out by a virtual radiography station using Monte Carlo simulation. In this simulated system, the neutron source has a cold spectrum; the diameter of the collimator is 4 cm at the narrowest part. The specimen is positioned 100 cm from the aperture. The scintillating screen is located 20 cm behind the object and the neutron radiation image is recorded by use of the ^{6}Li(n,a)-reaction. The test specimen is an aluminum cylinder which contains iron hoop, iron balls, screw, polyethylene rack, cadmium bar, and so forth. Figure 1(a) is the profile of the test specimen while Figure 1(b) is the corresponding neutron radiation image. The test specimen simulates the structure of an engine and has a good representative for the applications of neutron radiography in nondestructive testing.

In the comparative experiments, we employ the wavelet transform (WT), contourlet transform (CT), and the WDFB as the image sparse representation tools, respectively. Each of these sparse representation methods uses 9/7 biorthogonal filters and performs 3-level decomposition. As for the stage of direction analysis of CT and WDFB, we set the maximum direction as 8 at final scale. Meanwhile, in the L_1 optimization for CS reconstruction, OMP and TwIST based algorithms are compared. We called these schemes WT + OMP, WT + TwIST, CT + OMP, CT + TwIST, WDFB + OMP, and WDFB + TwIST, respectively. Table 1 shows the peak signal-to-noise ratio (PSNR, dB) of the reconstruction results using various schemes.

As can be seen from the table, in PSNR criteria, the schemes based on CT and WDFB outperform the WT-based

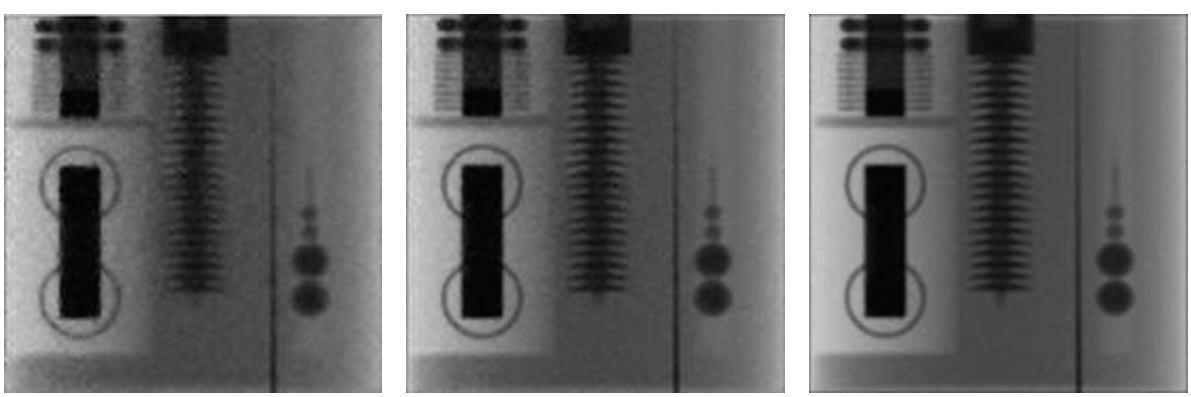
Table 1: Comparison of PSNR (dB) for the reconstruction results using various schemes.

Measurement ratios	WT + OMP	WT + TwIST	CT + OMP	CT + TwIST	WDFB + OMP	WDFB + TwIST
0.2	32.94	33.37	34.23	35.17	38.42	38.73
0.3	35.11	35.82	37.52	37.83	41.31	41.76
0.4	38.34	38.81	41.10	41.68	44.02	44.37
0.5	40.91	41.30	44.05	44.73	46.72	47.06



(a) Profile of the test specimen (b) Neutron radiation image

Figure 1: The test specimen and its neutron radiation image.



(a) Result of WT + OMP (b) Result of CT + OMP (c) Result of WDFB + TwIST

Figure 2: Reconstruction results for neutron radiation image using various methods.

counterpart. This indicates that CT and WDFB can represent the high dimensional singularity of image efficiently and suit the sparse representation of CS. Moreover, from the table we can also notice that, at low measurement ratio, the scheme based on WDFB has better performance. This is partly because WDFB can represent neutron radiation image more sparsely for its nonredundant characteristic. Regarding the solution of the L_1 optimization problem, the experiment results revealed that, compared with OMP, TwIST can further improve the quality of the reconstructed image; this is because OMP is a greedy algorithm, and it is difficult to avoid converging to local optimal.

The reconstruction results of the neutron radiation image using WT + OMP, CT + OMP, and WDFB + TwIST at measurement ratio = 0.2 were shown in Figure 2. The results showed that all three schemes can obtain ideal reconstruction image at measurement ratio = 0.2; therefore, it is feasible to reduce the sampling rate of digital neutron imaging system and data quantity of neutron radiation image by using CS technique. Through careful observation, we can notice that WT + OMP and CT + OMP based schemes can not preserve the details of original image and the reconstruction results are blurring with some "wrinkle" artifacts while the propose scheme can better preserve the image details. For preserving

the details of neutron radiation image critical in the nondestructive testing by means of neutron radiography, the experiments show the advantages of the proposed scheme. In addition, the above experiments were all implemented on a laptop computer with 2.26 GHz dual-core CPU, 2 MB RAM; in the view of the computational efficiency, the reconstruction times of WT + OMP, CT + OMP, and WDFB + TwIST schemes were 31.52 s, 33.35 s, and 27.23 s, respectively, at measurement ratio = 0.2. Therefore, the proposed scheme can greatly improve the computational efficiency and can meet the needs of practical applications.

6. Conclusions

With the advantages of multiscale geometric analysis and compressed sensing, this paper studies the compressed sensing technique for neutron radiation image and proposes a new block-based compressed sensing scheme. The scheme constructs a nonredundant multiscale geometry analysis transform named WDFB firstly, which not only inherits the high dimensional singularity representing ability of CT, but also overcomes the redundancy of the serious defects of the original CT. In the optimization process of CS, by adopting TwIST algorithm, the quality of the reconstructed image and the efficiency of the reconstruction algorithm were improved obviously. At present, as a new technology, the theoretical framework and implemental algorithm of CS are still evolving; the practical application of this technology has just started. In the future, we should explore the possibility of applying CS technology to the digital neutron imaging system to reduce the sampling rate of imaging system and the data volumes of neutron radiation image.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

The authors wish to thank F. Grunauer for providing some neutron radiation images. This work is supported in part by National Natural Science Foundation of China under Grants 61271399 and 61373068, Natural Science Foundation of Ningbo under Grant 2011A610192, Science and Technology Project of Ningbo under Grant 2013D10011, Science and Technology Innovation Team Project of Ningbo under Grant 2011B81002, and Open Fund for a Key-Discipline of Information and Communication Engineering of Zhejiang Province under Grant xkxl1425.

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