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Wavelet Denoising Algorithm Based on NDOA Compressed Sensing for Fluorescence Image of Microarray

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ABSTRACT A microarray can be easily used for quantitatively analyzing the expression levels of DNA genes. Yet, the noises introduced during the application will greatly affect the accuracy of DNA sequence detection. How to reduce the noise constitutes a challenging problem in microarray analysis. Especially, due to the weak fluorescence response, the image of microarray contains difficulties of the low peak-signal-to-noise ratio (PSNR) and luminance contrast. To solve the problem that the wavelet threshold denoising method has poor effective on low PSNR image, a wavelet denoising approach based on compression sensing (CS) optimized by the neural dynamics optimization algorithm (NDOA) is proposed, which preferably solves the denoising difficulties of noise pollution in the microarray image. Under the condition of Gaussian random observation matrix, the effectiveness of NDOA-optimized wavelet denoising based on CS gets better work than the orthogonal matching pursuit and its improved algorithms. The experimental results indicate that the expected wavelet coefficients of the noiseless image have been reconstructed with higher quality. When the compression sampling rate for microarray image is 0.875, the PSNR of the NDOA-optimized wavelet denoising algorithm based on CS is increased about 9 dB, and the root mean squared error is reduced obviously too, in comparison with the wavelet soft-threshold denoising method. It shows that the NDOA-optimized method improves the performance of the classical wavelet threshold denoising.

INDEX TERMS Compressed sensing, wavelet denoising, DNA microarray, image filtering, NDOA.

I. INTRODUCTION

As one of the great advances in modern technology, a DNA microarray was designed to detect specific gene sequences, which were developed as probes fixed at specified positions to perform a large number of different hybridization experiments simultaneously on a single glass substrate. It's well-suited to quantitatively compare the expression levels of many genes, as well as easily used for qualitative detection to study the DNA sequences [1], [2].

In the process of microarray scanning, the excitation spectra of probes induced from the fluorescence dye are usually stored as 16-bit TIFF by the scanner [3]. However, due to the weak fluorescence response, complex biochemical reaction, imperfections in glass slide and photoelectric sensor conversion distortion, etc, the signal of fluorescence probe is inevitably degraded, which leads to serious noise interference in the microarray image. This contamination will directly affect the accuracy of quantitative analysis [4], [5].

Therefore the image filtering algorithm emerges as an important issue in biochip quantitative application. Yet, only a few efforts have focused on this specific problem. Adjeroh *et al.* [6] presented a method based on a modified form of the translation invariant Wavelet. It performed the horizontal, vertical and diagonal shift images, and then the resultant and original images were wavelet-transformed, thresholded independently and shifted back. The final denoised image was obtained by taking a median of the four reconstructed images. In [7], a new Wavelet method to deal with microarray denoised image was proposed based on stationary Wavelets (SWT) and soft-threshold analysis. In fact, Wavelet theory and thresholding technique are the beneficial method to provide an enhanced approach for eliminating noise and ensuring a better image quality. Unfortunately, it is difficult to look for an optimal threshold to reduce the signal noise perfectly, although the principle of threshold denoising method is very simple. And then this shortcoming has restricted the implementation of Wavelet threshold filtering technique. Mastriani and Giraldez [8] even proposed a wavelet-based denoising via smoothing of coefficients to avoid the threshold selection. In allusion to this problem, the compressed sensing (CS) and sparse representation theory have provided a more effective way for signal denoising than the Wavelet threshold denoising algorithm [9], [10].

As well known, the image under Wavelet transform (WT) has sparse properties, even though the sparsity of Wavelet coefficients will be greatly reduced when the signal is noisy. According to CS theory, the original or clean signal can be reconstructed from a small amount of the projection coefficients by an appropriate optimization algorithm [11], [12]. Therefore, we can rely on CS to reconstruct the sparsity of Wavelet coefficients, which not only avoids optimizing threshold in Wavelet threshold filter, but also recovers the Wavelet coefficients with most sparse representation and without losing important information. That is, a new denoising method for sparse signal based on CS could be applied for achieving the high quality image.

This CS filtering system includes three parts: sparse transform, compression sampling and signal reconstruction. Among them, CS reconstruction for sparse signal is the most important step [9]. In CS theory, the approximate solution is usually obtained by solving the l_1-norm [13], [14]. And there are many ways to take the optimal solutions for CS reconstruction, including greedy algorithm, convex optimization algorithm and so on [15], [16]. As a global optimum approximation, NDOA introduces energy function to solve the convex optimization problem by transforming the energy function into the corresponding global convergent differential equations, which has the advantages of parallel computation and suitable for software and hardware implementation. Furthermore, the effectiveness of NDOA-optimized reconstruction of CS gets better work than the orthogonal matching pursuit (OMP) and its improved algorithms, such as regularized orthogonal matching pursuit (ROMP), stagewise weak OMP (SWOMP) and subspace pursuit (SP), etc [17]. It has obvious application advantages in many image processing fields.

Our work employs a novel Wavelet filtering technique based on CS optimized by the NDOA, whose results show that the designed denoising method is superior and effective. The rest of the paper is organized as follows: the related knowledge about CS theory, Wavelet filtering technique and NDOA model are introduced in Section II. And then, experimental results and analyses are given in Section III. Finally, conclusion and discussion are drawn in Section IV.

II. WAVELET DENOISING ALGORITHM BASED ON NDOA COMPRESSED SENSING

Image denoising algorithm has received considerable attention in various fields. Most of the conventional filtering techniques, such as mean filter, Gaussian filter and minimum mean squared error filter, cannot always guarantee the acceptable quality of denoised image with the high peak signal noise ratio (PSNR) and so on [18], [19]. In recent decades, the discrete Wavelet transform (DWT) has been applied to dispose the problem of noise reduction, and it has been shown to be outperformed to traditional filters in terms of root mean squared error (RMSE), PSNR and other evaluation indicators [9], [20].

The Wavelet denoising algorithm has been well acknowledged as an important method. In mathematics, the essence of Wavelet denoising is a function approximation problem. In other words, that is how to find the best approximation of the original signal in the Wavelet space developed by the scaling and translation of the Wavelet generating function, according to the proposed criteria, so as to achieve the complete distinction between the original signal and the noise signal. Compared with noise feature, the larger amplitude in Wavelet domain is the coefficients with important signal characteristics, while the amplitude of noise coefficients is smaller [21]. Therefore, the Wavelet coefficients with larger absolute value can be retained or contracted only by setting an appropriate threshold and the estimated Wavelet coefficients (EWC) has been obtained.

For the two-dimensional (2D) case, Wavelet denoising algorithm transforms the image to time-frequency domain under DWT processing, then we could keep only some large coefficients and throw away the rest using a properly threshold-level, too. The result is that a small number of largest coefficients which has key information are saved while most noise coefficients that are small will be discarded, and the so-called image EWC is emerged. If we reconstruct the image from this EWC, the noise would be reduced effectively [22]. Despite the many advantages, there is also difficult to research the optimal threshold level to form the image EWC [23].

A. COMPRESSED SENSING

The CS theory which was put forward by Donoho, Candes, Tao and others, has offered a framework for the detection of sparse signals with a reduced number of samples [24].

This theory can realize the perfect reconstruction of the original signal at a rate far below Nyquist, and it provides a strong support for the accurate recovery of sparse signals.

Consider a digital signal $f \in R^N$ and expressed as $x = \psi^T f$, while x is K-sparse in the orthogonal basis $\psi \in R^{N\times N}$. If an observation matrix $\varphi \in R^{M\times N}$ and $M << N$ is designed, the CS expression would be shown as following [25].

$$y = \varphi f = \varphi\psi x = Ax \tag{1}$$

Obviously, there is an underdetermined system.

Since the x is K-sparse, the freedom of x is only K + 1 degree. Thus the accurate recovery of x could be obtained by some nonlinear algorithms when the number of observations is no less than K + 1. The CS theory has pointed out that the signal x would be reconstructed with an observation matrix by minimizing the following type of l_0-norm.

$$\min \ \|x\|_0 \quad s.t. \ y = Ax \tag{2}$$

where $\|x\|_0$ denoted as l_0-norm.

Unfortunately, solving the l_0-norm is known as NP-hard. In order to keep away from this problem, it is usually converted (2) into the minimizing l_1-norm with optimization constraints. As long as the observation matrix A, such as Gaussian observation matrix, satisfies the restricted isometric property (RIP), the (1) would agree with the following constraints [26]

$$\hat{x} = \arg\min \ \|x\|_1 \quad s.t. \ y = Ax \tag{3}$$

where $\|x\|_1 = \sum \mid x_i \mid$ with $i = 1,2,\ldots, N$, denoted as l_1-norm.

B. WAVELET DENOISING BASED ON COMPRESSED SENSING

The CS flitting system is composed of sparse transform, compression sampling and signal reconstruction, which is shown in Figure 1 [9].

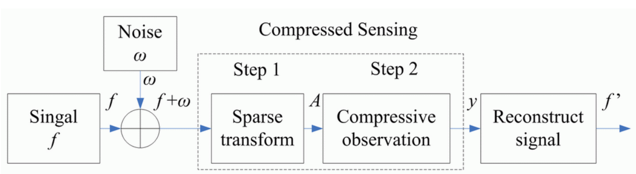


FIGURE 1. Denoising model based on compressed sensing.

Generally, The Mallat algorithm is often used to form the sparse transform. And that the Wavelet coefficients of noiseless signals obtained by Mallat have sparsity. If there is noisy, the sparsity of Wavelet coefficients can be greatly reduced. Based on the above foundation of CS theory and sparse features, we can reconstruct the sparsity of Wavelet coefficients and achieve the denoising signals with high-quality.

The basic idea of CS denoising algorithm is introduced below. If the noise ω is taken into account, the mixed signal of $f+\omega$ will no longer be completely sparse in Wavelet domain. But if we still make the signal $f+\omega$ compress by φ, the (4) would be obtained as

$$y = \varphi\,(f+\omega) = \varphi\psi x + \varphi\omega = Ax + w \tag{4}$$

This shows that the measured value y is influenced by the noise w [26].

When the CS matrix A satisfies the RIP, the (4) will also satisfy the following constraints

$$\min \ \|x\|_1 \quad s.t. \ \|Ax - y\|_2 \le \delta \tag{5}$$

The (5) could be simply transformed into the constraint of solution

$$\min \ \|Ax - y\|_2 \quad s.t. \ \|x\|_1 \le \tau \tag{6}$$

where τ is denoted as an arithmetic number and δ is a small threshold related to the standard deviation of noise [26].

When Lagrange factor λ is used to solve the unconstrained convex programming, there is an equivalent expression for (5) as following [27]

$$\min \left(\frac{1}{2}\,\|Ax - y\|_2^2 + \lambda\,\|x\|_1\right) \tag{7}$$

In the next step, we could divide the sparse signal x into two parts, namely, the positive elements u and the negative elements v. And define $X = u - v$, where $u_i = (x_i)^+ = \max\{0, x_i\}$ and $v_i = (-x_i)^+ = \max\{0, -x_i\}$. Then the $\|X\|_1$ can be expressed as $\|X\|_1 = 1_N^T u + 1_N^T v$ while $1_N^T = [1\cdots 1]_N$ [17]. Therefore, refer to (7), there is

$$\min \left[\frac{1}{2}\,\|A(u-v) - y\|_2^2 + \lambda(1_N^T u + 1_N^T v)\right] \tag{8}$$

Considering the $z = [u, v]^{\mathrm{T}}$ and $z \ge 0$, the constrained quadratic program could be expressed as

$$\min F(z) = \arg\min(c^T z + \frac{1}{2} z^T Bz), \quad z \ge 0 \tag{9}$$

where $B = \begin{bmatrix} A^T A & -A^T A \\ -A^T A & A^T A \end{bmatrix}$, $c = \lambda 1_{2N} + \begin{bmatrix} A^T y \\ -A^T y \end{bmatrix}$.

Since $z = [u \quad v]^{\mathrm{T}}$, the optimal sparse solution of (9) could be produced from $X = u - v$.

C. CONSTRAINED OPTIMIZATION MODEL BASED ON NDOA

The NDOA provides a powerful tool to solve the constrained optimization of linear programming (LP) and quadratic programming (QP) problems [28]. When we are concerned with these problems like (9), there is

$$\min(\frac{1}{2} z^T Bz + c^T z) \quad \text{s.t. } Dz = b, \quad z \ge 0 \tag{10}$$

And its dual form is

$$\max(b^T y - \frac{1}{2} z^T Bz) \quad \text{s.t. } D^T y - Bz \le c \tag{11}$$

where $D^{M\times N}$ was a real matrix and $B^{N\times N}$ was a real symmetric positive semi-definite matrix, while $M << N$, $z, c \in R^N$, and $y, b \in R^M$.

Assuming that $(z_i)^+ = \max\{0, z_i\}$ and $i = 1,\ldots, N$. According to literature [29], we could obtain the neural network model as

$$\frac{\mathrm{d}}{\mathrm{d}t}\begin{pmatrix} z \\ y \end{pmatrix} = -\begin{bmatrix} (I+B)[z-(z+D^T y - Bz - c)]^+ + D^T(Dz-b) \\ -D[z-(z+D^T y - Bz - c)^+] + Dz - b \end{bmatrix} \tag{12}$$

where I was a unit matrix, and the solution of (12) is a global optimal solution of (10) and (11).

D. IMAGE RECONSTRUCTION OF CS BASED ON NDOA

Suppose an image $F \in R^{N\times N}$ that can be represented as $X = WFW^T$, where X is sparse in the orthogonal basis $W \in R^{N\times N}$. If the $\Phi \in R^{M\times N}$ is designed as a CS's observation matrix for each column of 2D image, the observation vector $Y \in R^{M\times N}$ would be expressed as

$$Y = \Phi F = \Phi W^T X W = \Theta X W \tag{13}$$

And there is

$$YW^T = \Phi F W^T = \Phi W^T X = \Theta X \tag{14}$$

When the normalized matrix Φ is subjected to Gaussian distribution, the $\Theta = \Phi W^T$ will satisfy RIP with high probability. Therefore, the $F = W^T X W$ can be reconstructed by each column vector $x_j \in R^{N\times 1}$, while $X \in R^{N\times N}$, with the observation matrix $\Theta \in R^{M\times N}$ based on CS theory. And (14) would be to relax as an l_1-norm optimization problem

$$\min \left\|x_j\right\|_1 \quad s.t.\ YW^T = \Theta X, \quad j \in [1, N] \tag{15}$$

In (15), we could also divide the sparse signal x_j into two parts, positive elements and negative elements, just as (8). So $X = p - q$, where $p_j = (x_{ji})^+ = \max\{0, x_{ji}\}$ and $q_j = (-x_{ji})^+ = \max\{0, -x_{ji}\}$. Therefore, YW^T could be written as

$$YW^T = \Theta X = \Theta(p-q) = [\,\Theta \quad -\Theta\,]\begin{bmatrix} p \\ q \end{bmatrix} \tag{16}$$

Then a constrained convex optimization model was wrote to solve (15), and shown as

$$\begin{cases} \min\ F(u) = \min(c^T u) \\ s.t.\ Du = b \\ \quad u \geq 0 \end{cases} \tag{17}$$

where $u = \begin{bmatrix} p \\ q \end{bmatrix}$, $c = 1_{2N}$, $D = [\,\Theta \quad -\Theta\,]$ and $b = YW^T$.

Correspondingly, its dual form is

$$\begin{cases} \max\ (b^T v) \\ s.t.\ D^T v \leq c \end{cases} \tag{18}$$

And we could also obtain the neural network model as

$$\frac{\mathrm{d}}{\mathrm{d}t}\begin{pmatrix} u \\ v \end{pmatrix} = -\begin{bmatrix} u-(u+D^T v - c)^+ + D^T(Du-b) \\ D(u+D^T v - c)^+] - b \end{bmatrix} \tag{19}$$

At the same time, the classical Runge-Kutta method is a suitable approach to solve these differential equations [23]. And the optimal sparse solution also can be produced from $X = p - q$, with $u = [p\ q]^{\mathrm{T}}$.

III. EXPERIMENT RESULTS AND ANALYSES

Microarray contains a series of probes which have lots of DNA fragments on a small piece of glass. In order to eliminate the brightness interference caused by imperceptible flaws, a morphological filter with circular structural element and multiple filtering strategy has been firstly designed as $[f \circ (f \bullet b) + f \bullet (f \circ b)]/2$.

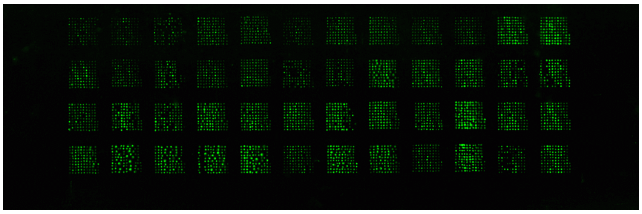


FIGURE 2. Morphological denoising result of Cy3 response of microarray provided by Fuzhou University.

Figure 2 shows the morphological result of Cy3 response image of microarray provided by Fuzhou University [30].

When we take the P[2,5] sub-array from the fluorescence image in Figure 2, called P[2,5] sub-image, we could apply Mallat algorithm to decompose this sub-image into four sectors, denoted as LL, LH, LV and LD, under the Sym8 WT, as shown in Figure 3.

If we deal with high-frequency LH, LV and LD coefficients with soft-thresholds according to the noise features independently, the Wavelet soft-threshold denoising reconstruction could be obtained from EWC of LH, LV and LD. And the finally reconstruction is indicated in Figure 4.

Furthermore, considering high accuracy reconstruction of EWC by CS method, we will further research the denoising performances of Wavelet filter based on CS by using OMP, SWOMP and NDOA method. In the course of discussing, we have applied observation matrix of Gaussian random matrix to achieve observation coefficients under the compression sampling ratio $\eta = 0.875$ in WT domain, and we also have reconstructed the denoising coefficients of high-frequency sector, namely LH, LV and LD. For the sake of discussion, they are demonstrated in Figure 5, Figure 6 and Figure 7, which have been reconstructed by CS using OMP, SWOMP and NDOA, respectively.

Then we could obtain the denoised image by the inverse Wavelet transform and draw the fitting performance at the same time. Coefficients reconstruction images of Wavelet denoising based on CS processed by OMP, SWOMP and NDOA respectively, are shown in Figure 8.

In order to compare the performance of Wavelet denoising algorithm conveniently, Table 1 shows the comparison of PSNR and RMSE of the different denoising algorithm.

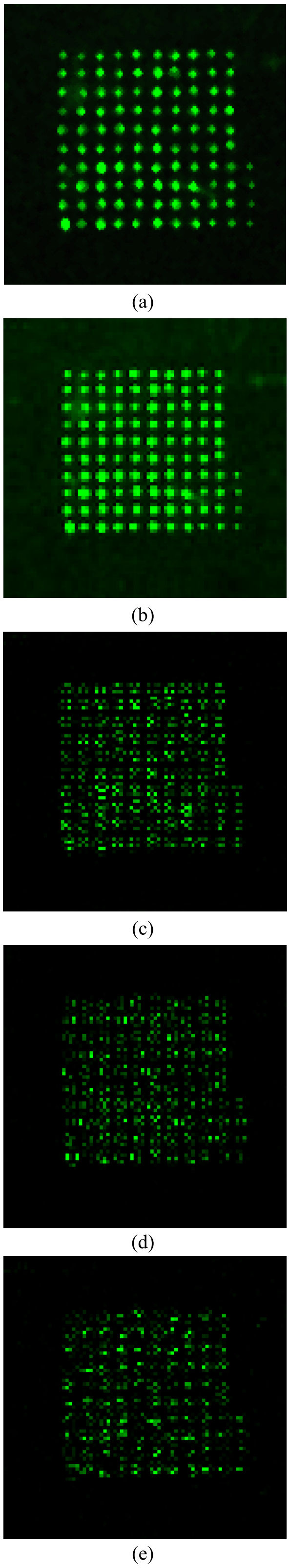


FIGURE 3. Original image and the wavelet decomposition of P[2,5] by Sym8 wavelet transform. (a) Original image of P[2,5], (b) LL distribution of WT, (c) LH distribution of WT, (d) LV distribution of WT, and (e) LD distribution of WT.

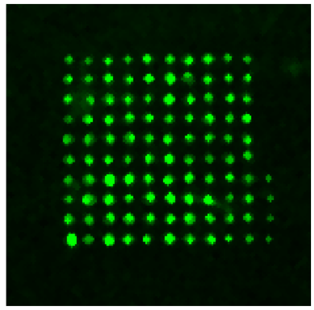


FIGURE 4. Reconstruction image of wavelet soft-threshold denoising method for P[2,5] sub-array.

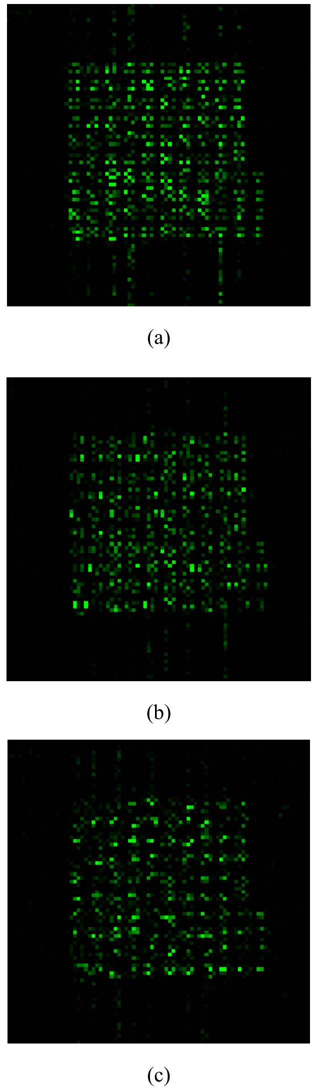
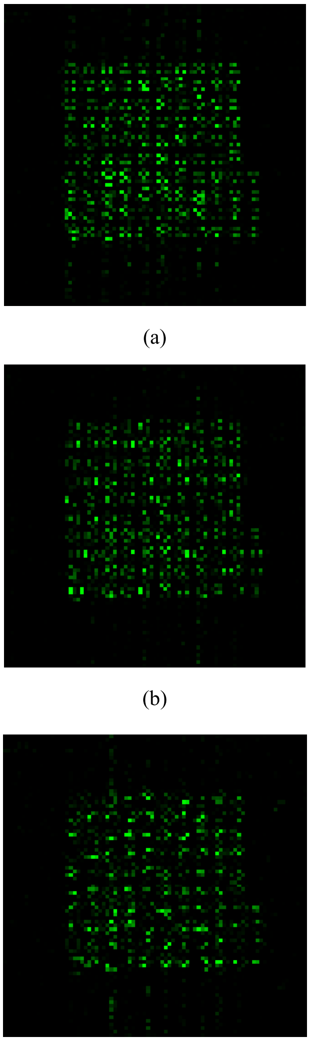


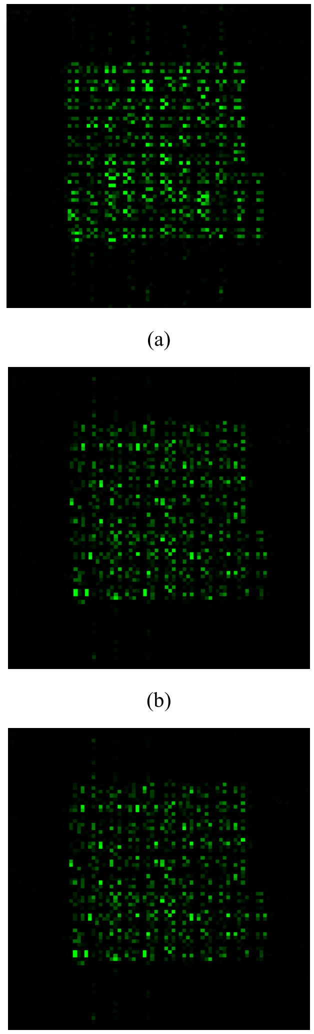
FIGURE 5. Reconstruct denoising coefficients of high-frequency sector by OMP based on CS. (a) LH reconstructed by OMP, (b) LV reconstructed by OMP, and (c) LD reconstructed by OMP.

From the statistical results in Table 1, either CS algorithm based on NDOA, SWOMP and OMP or Wavelet filtering method of soft-threshold, has been done well in image



(a) (b) (c)

FIGURE 6. Reconstruct denoising coefficients of high-frequency sector by SWOMP based on CS. (a) LH reconstructed by SWOMP, (b) LV reconstructed by SWOMP, and (c) LD reconstructed by SWOMP.



(a) (b) (c)

FIGURE 7. Reconstruct denoising coefficients of high-frequency sector by NDOA based on CS. (a) LH reconstructed by NDOA, (b) LV reconstructed by NDOA, and (c) LD reconstructed by NDOA.

TABLE 1. Performance comparison of the different denoising algorithms.

0 level image	Reconstruction algorithm	Compression sampling	PSNR (dB)	RMSE
P[2,5] Image of Microarray	WT Filtering of Soft-threshold	/	40.45	622.1
	OMP	η=0.875	46.68	303.6
	SWOMP	η=0.875	47.08	290.0
	NDOA	η=0.875	49.33	223.8

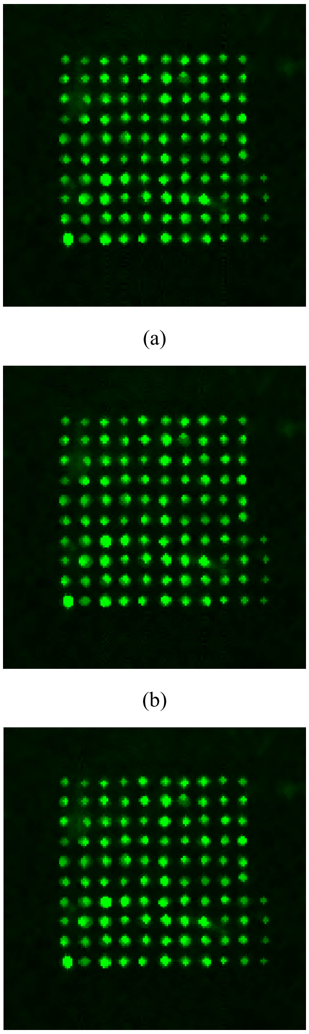
TABLE 2. Denoising performance comparison of different sampling rates.

0 level image	Reconstruction algorithm	Compression sampling	PSNR (dB)	RMSE
P[2,5] Image of Microarray	WT Filtering of Soft-threshold	/	40.45	622.1
	SWOMP	0.875	47.08	290.0
	SWOMP	0.500	34.58	1224.7
	SWOMP	0.125	31.17	1808.3

of microarray. Additionally, in the case of compression sampling ratio $\eta = 0.875$, the PSNR of Wavelet denoising algorithm based on NDOA is increased about 9dB and the RMSE is also reduced significantly, compared with the Wavelet soft-threshold filtering method.

Meanwhile, in order to investigate the effect resulting from compression sampling rates on Wavelet deniosing algorithm, we try to reduce the noise at sampling rates of 0.875, 0.50 and 0.125 for the same image. We notify that the relatively consistent denoising trend of OMP, SWOMP and NDOA at different compression sampling rate. Simply, Table 2 only demonstrates the PSNR and RMSE corresponding to the SWOMP algorithm to illustrate the trend under different compression sampling rates.

According to the Table 2, it shows that the decrease of compression sampling rates, the more information lost in the sampling process of Wavelet coefficients, and thus a larger deviation is produced in signal reconstruction. That is to say,



(a)

(b)

(c)

FIGURE 8. **Reconstruct denoised images of different recovery method based on CS. (a) Denoised image by OMP based on CS, (b) Denoised image by SWOMP based on CS, and (c) Denoised image by NDOA based on CS.**

if the compression sampling rate is small, the performance of Wavelet filtering algorithm based on CS is worse. On the contrary, in order to ensure the better filtering effect, a high compression sampling rate needs to be selected.

IV. SUMMARY AND CONCLUSIONS

The fluorescence response of microarray is so weak that the noises would affect the image quality seriously. Moreover, the Wavelet soft-threshold denoising algorithm has poor effective on this low PSNR image. Considering that the CS theory provides a more effective method for reconstruction of perfect sparse coefficients despite the noise pollution in Wavelet domain, it not only avoids the problem of threshold estimation, but also recovers the completely sparse representation of Wavelet coefficients. Especially, the NDOA-optimized Wavelet denoising method based on CS has achieved good results. When the compressed sampling rate is 0.875 for microarray image, compared with the traditional Wavelet soft-threshold denoising algorithm, the RMSE is reduced significantly and the PSNR is increased about 9dB. The results show that the NDOA-optimized denoising method improves the effectiveness in reducing the noise of microarray images.

Although the NDOA-optimized denoising method has good performance for low PSNR image, we still have the challenge of computational complexity of CS reconstruction based on NDOA. Fortunately, the parallel computation by hardware or software would be an effective way to solve this problem, so the hardware implementation and the software parallel operation of Wavelet denoising based on CS optimized by NDOA will need to be further studied to improve the real-time performance.

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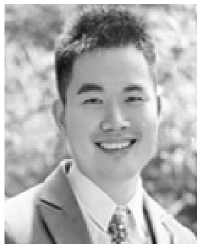

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