



Soldering & Surface Mount Technology

Solder joint imagery compressing and recovery based on compressive sensing
Huihuang Zhao Yaonan Wang Zhijun Qiao Bin Fu

Article information:

To cite this document:

Huihuang Zhao Yaonan Wang Zhijun Qiao Bin Fu , (2014), "Solder joint imagery compressing and recovery based on compressive sensing", Soldering & Surface Mount Technology, Vol. 26 Iss 3 pp. 129 - 138

Permanent link to this document:

<http://dx.doi.org/10.1108/SSMT-09-2013-0024>

Downloaded on: 10 May 2016, At: 18:40 (PT)

References: this document contains references to 30 other documents.

To copy this document: permissions@emeraldinsight.com

The fulltext of this document has been downloaded 54 times since 2014*

Users who downloaded this article also downloaded:

(2014), "Lifetime prediction and design aspects of reliable lead-free non-collapsible BGA joints in LTCC packages for RF/microwave telecommunication applications", Soldering & Surface Mount Technology, Vol. 26 Iss 3 pp. 117-128 <http://dx.doi.org/10.1108/SSMT-07-2013-0018>

(2014), "Review on the effect of alloying element and nanoparticle additions on the properties of Sn-Ag-Cu solder alloys", Soldering & Surface Mount Technology, Vol. 26 Iss 3 pp. 147-161 <http://dx.doi.org/10.1108/SSMT-02-2014-0001>

(2014), "A method for the tin pest presence testing in SnCu solder alloys", Soldering & Surface Mount Technology, Vol. 26 Iss 3 pp. 110-116 <http://dx.doi.org/10.1108/SSMT-10-2013-0027>

Access to this document was granted through an Emerald subscription provided by Token:JournalAuthor:B342F257-D1B1-4AFD-AA7F-763A98493F67:

For Authors

If you would like to write for this, or any other Emerald publication, then please use our Emerald for Authors service information about how to choose which publication to write for and submission guidelines are available for all. Please visit www.emeraldinsight.com/authors for more information.

About Emerald www.emeraldinsight.com

Emerald is a global publisher linking research and practice to the benefit of society. The company manages a portfolio of more than 290 journals and over 2,350 books and book series volumes, as well as providing an extensive range of online products and additional customer resources and services.

Emerald is both COUNTER 4 and TRANSFER compliant. The organization is a partner of the Committee on Publication Ethics (COPE) and also works with Portico and the LOCKSS initiative for digital archive preservation.

*Related content and download information correct at time of download.

Solder joint imagery compressing and recovery based on compressive sensing

Huihuang Zhao

College of Electrical and Information Engineering, Hunan University, ChangSha, China and
Department of Computer Science, HengYang Normal University, HengYang, China

Yaonan Wang

College of Electrical and Information Engineering, Hunan University, ChangSha, China, and

Zhijun Qiao and Bin Fu

Department of Mathematics, University of Texas-Pan American, Texas, USA

Abstract

Purpose – The purpose of this paper is to develop an improved compressive sensing algorithm for solder joint imagery compressing and recovery. The improved algorithm can improve the performance in terms of peak signal to noise ratio (PSNR) of solder joint imagery recovery.

Design/methodology/approach – Unlike the traditional method, at first, the image was transformed into a sparse signal by discrete cosine transform; then the solder joint image was divided into blocks, and each image block was transformed into a one-dimensional data vector. At last, a block compressive sampling matching pursuit was proposed, and the proposed algorithm with different block sizes was used in recovering the solder joint imagery.

Findings – The experiments showed that the proposed algorithm could achieve the best results on PSNR when compared to other methods such as the orthogonal matching pursuit algorithm, greedy basis pursuit algorithm, subspace pursuit algorithm and compressive sampling matching pursuit algorithm. When the block size was 16×16 , the proposed algorithm could obtain better results than when the block size was 8×8 and 4×4 .

Practical implications – The paper provides a methodology for solder joint imagery compressing and recovery, and the proposed algorithm can also be used in other image compressing and recovery applications.

Originality/value – According to the compressed sensing (CS) theory, a sparse or compressible signal can be represented by a fewer number of bases than those required by the Nyquist theorem. The findings provide fundamental guidelines to improve performance in image compressing and recovery based on compressive sensing.

Keywords Assembly, Solder joints, Solder, Pin-in-paste

Paper type Research paper

1. Introduction

Compressed sensing (CS) is a sampling paradigm that provides the signal compression at a rate significantly lower than the Nyquist rate. Based on the CS theory, a sparse or compressible signal can be represented by a smaller number of bases than those required by the Nyquist theorem when it is mapped to the space with bases incoherent to the sparse data space (Donoho, 2006; Donoho *et al.*, 2006). The contents of most references are about imagery and raw data compressing and reconstruction based on the CS theory. CS has been successfully applied to magnetic resonance imaging (Lustig *et al.*, 2007), with consistent benefits in a clinical setting (Vasanawala *et al.*, 2010). In a study by Jørgensen *et al.* (2012), an iterative image reconstruction method in X-ray computed tomography (CT) was proposed based on

compressive sensing (CS). Bhattacharya *et al.* (2007) proposes a new method of fast encoding for synthetic aperture radar (SAR) raw data by using the CS theory to complete SAR raw data compressing and reconstruction.

Nowadays, surface mount technology (SMT) components are widely used in the electronics industry. To detect surface-related defects such as pseudo solder, which is not a hidden open joint (Wu and Zhang, 2011), insufficient solder, component shift, wrong component use and tombstoning (Janoczki *et al.*, 2010), automatic inspection technologies, such as automatic optical inspection (AOI) and X-ray inspection, have been applied to SMT-based production and proved to be a useful supplement to circuit and functional testing (Hongwei *et al.*, 2011; Benedek *et al.*, 2013). To improve the inspection rate of defects, some image processing technologies, such as image compression, image enhancing and image filtering are used in AOI and SPI (Xiong *et al.*, 2012). Usually, wavelet transform and wavelet package transform are used in image compression (Karami *et al.*, 2012; Bayazit, 2011). Due to the steadily increasing resolution of the image acquisition platforms, the amount of image data produced is now constrained by storage capabilities and the slow

The current issue and full text archive of this journal is available at
www.emeraldinsight.com/0954-0911.htm



Soldering & Surface Mount Technology
26/3 (2014) 129–138
© Emerald Group Publishing Limited [ISSN 0954-0911]
[DOI 10.1108/SSMT-09-2013-0024]

The authors appreciate the careful comments of the anonymous reviewers. This work was supported by Key Construction Disciplines of the Hunan Province during the 12th Five-Year Plan period.

inspection speed (Wu *et al.*, 2013). Also, CS can be used in SMT, such as solder joint inspection, solder joint image processing and so on. There are few references about solder joint imagery data compressing and reconstruction based on the CS theory. In this paper, solder joint imagery data compressing and reconstruction based on CS have been studied.

This paper is organized as follows. In Section 2, the CS theory is presented. The signal recovery algorithms are presented in Section 3, and then some CS recovery algorithms are described in detail. The methodology of this paper and the block compressive sampling matching pursuit (CoSaMP) algorithm are presented in Section 4. Experimental results were obtained with the proposed method using solder images in Section 5. Finally, the conclusions are summarized at the end of this paper.

2. CS theory

2.1 Compressed sensing

CS is based on the assumption of the sparse property of a signal and incoherency between the bases of sparse domain and the bases of measurement vectors. CS has three major steps:

- 1 the construction of k -sparse representation;
- 2 the compression; and
- 3 the reconstruction.

The first step is the construction of k -sparse representation, where k is the number of the non-zero entries of the sparse signal. Most natural signals can be made sparse by applying orthogonal transforms such as wavelet transform, fast Fourier transform and discrete cosine transform (DCT). This step is represented as (Candes and Wakin, 2008):

$$s = \Psi^T x \quad (1)$$

where x is an N -dimensional non-sparse signal, s is a weighted N -dimensional vector (sparse signal with k non-zero elements) and Ψ is an $N \times N$ orthogonal basis matrix. The second step is compression. In this step, the random measurement matrix is applied to the sparse signal according to the following equation:

$$y = \Phi s = \Phi \Psi^T x \quad (2)$$

where Φ is an $M \times N$ random measurement matrix ($M < N$).

Let M be the number of measurements (the row dimension of y) sufficient for a high probability of successful reconstruction, and M is determined by:

$$M \geq C \mu^2(\Phi, \Psi) k \log N \quad (3)$$

For some positive constant C , $\mu(\Phi, \Psi)$ is the coherence between Φ and Ψ and is defined by:

$$\mu(\Phi, \Psi) = \sqrt{N} \max_{i,j} |\langle \phi_i, \psi_j \rangle| \quad (4)$$

If the elements in ϕ and ψ are correlated, the coherence is large. Otherwise, it is small. From linear algebra, it is known that $\mu(\Phi, \Psi) \in [1, \sqrt{N}]$.

2.2 Reconstruction method

Successful reconstruction depends on the measurement matrix Φ that complies with restricted isometry property (RIP). RIP is defined as follows (Cai and Wang, 2011):

$$(1 - \delta_k) \|s\|_2^2 \leq \|\Phi s\|_2^2 \leq (1 + \delta_k) \|s\|_2^2 \quad (5)$$

where $\|\cdot\|_2$ defines the L_2 norm and δ_k is the k -restricted isometry constant of a matrix Φ . RIP is used to ensure that all subsets of k columns taken from Φ are nearly orthogonal. It should be noted that Φ has more columns than rows; thus, Φ cannot be exactly orthogonal.

The reconstruction is the optimization problem to solve (2). In (2), when Ψ is an identity matrix. The following equation is the reconstruction problem used in this study:

$$\arg \max_x \|x\|_0 \text{ s.t. } y = \Phi x \quad (6)$$

3. Signal recovery algorithm

The major algorithmic challenge in compressive sampling is to approximate a signal, given a vector of samples. The literature describes a huge number of approaches to solving this problem. They fall into three rough categories:

- 1 *Convex optimization*: These techniques solve a convex program whose minimizer is known to approximate the target signal. Many algorithms have been proposed to complete the optimization, including basis pursuit (BP) (Bazerque and Giannakis, 2013), projected gradient methods (Figueiredo *et al.*, 2007) and iterative hard thresholding (Blumensath and Davies, 2009).
- 2 *Iterative greedy algorithms*: These methods build up an approximation one step at a time by making locally optimal choices at each step. Examples include matching pursuit (MP) (Tropp and Gilbert, 2007), orthogonal matching pursuit (OMP), regularized OMP (Needell *et al.*, 2009), stage-wise OMP (StOMP) (D. L. Donoho *et al.*, 2012) and CoSaMP (Needell *et al.*, 2010).
- 3 *Combinatorial algorithms*: These methods acquire highly structured samples of the signal that support rapid reconstruction via group testing. This class includes Fourier sampling (A. Gilbert *et al.*, 2007), HHS pursuit (Gilbert *et al.*, 2005) and Iwen (Iwen, 2008).

Here, attention is focused on the OMP algorithm, greedy basis pursuit (GBP) algorithm, subspace pursuit (SP) algorithm and CoSaMP algorithm (Davenport *et al.*, 2013).

3.1 Orthogonal matching pursuit

OMP is an iterative greedy algorithm that selects, at each step, the column of measurement matrix which is most correlated with the current residuals. This column is then added into the set of selected columns. The algorithm updates the residuals by projecting the observation onto the linear subspace spanned by the columns that have already been selected, and the algorithm then iterates. Compared with other alternative methods, a major advantage of the OMP is its simplicity and fast implementation. The following lists the steps of the OMP algorithm.

Algorithm 1. OMP recovery algorithm

Input:

An $m \times N$ measurement matrix Φ , an m -dimensional data vector v and the sparsity level s of the ideal signal.

Initialization:

Initialize the residual $r_0 = v$, the index set $\Lambda_0 = \emptyset$ and the iteration counter $t = 1$.

Procedure:

- 1 Find the index λ_t that solves the easy optimization problem:

$$\lambda_t = \arg \max_{j=1, \dots, d} |\langle r_{t-1}, \varphi_j \rangle|$$

If the maximum occurs for multiple indices, break the tie deterministically.

- 2 Augment the index set and the matrix of chosen atoms: $\Lambda_t = \Lambda_{t-1} \cup \{\lambda_t\}$ and $\Phi_t = [\Phi_{t-1} \ \varphi_{\lambda_t}]$. We use the convention that Φ_0 is an empty matrix.
- 3 Solve a least squares problem to obtain a new signal estimate:

$$x_t = \arg \min_x \|v - \Phi_t x\|_2$$

- 4 Calculate the new approximation of the data and the new residual:

$$a_t = \Phi_t x_t; r_t = v - a_t$$

- 5 Increment t and return to step (2) if $t < m$ or $r_{t-1} = 0$.
- 6 The estimate \hat{s} for the ideal signal has non-zero indices at the components listed in Λ_m . The value of the estimate \hat{s} in component λ_j equals the j th component of x_r .
End

Output:

An estimate \hat{s} in $M \times d$ matrix R^d for the ideal signal, a set Λ_m containing m elements from $\{1, \dots, d\}$ and an N -dimensional approximation a_m of the data vector v .

3.2 Greedy basis pursuit

GBP is rooted in computational geometry and exploits an equivalence between minimizing the l^1 -norm of the representation coefficients and determining the intersection of the signal with the convex hull of the dictionary. GBP unifies the different advantages of previous algorithms. It builds up representations, sequentially selecting atoms. The following lists the steps of the GBP algorithm.

Algorithm 2: CS recovery using GBP

Input:

A signal $x \in R^d$, a dictionary $D = \{\psi_i\}_{i=1}^n$, $\|\psi_i\|_2 = 1$ and a threshold $\varepsilon \geq 0$; a representation of x , consisting of a set of indices $I \subseteq \{1, \dots, n\}$ and a set of coefficients $A = \{\alpha_i\}_{i \in I}$, such that $x - \sum_{i \in I} \alpha_i \psi_i < \varepsilon$.

Procedure:

Initialize:

- 1 Select the first atom:

$$k = \arg \max_{i \in \{1, \dots, n\}} \langle x, \psi_i \rangle$$

- 2 Compute the initial approximation:

$$\alpha_k = \langle x, \psi_k \rangle, I^{(0)} = \{k\}, A^{(0)} = \{\alpha_k\};$$

- 3 Initialize the biorthogonal system:

$$\tilde{\Psi}^\perp = \{\psi_k\}$$

- 4 Initialize the hyperplane:

$$\tilde{x}^{(0)} = \alpha_k \psi_k, n = x / \|x\|, r = x - \tilde{x}$$

Repeat until:

- 1 Compute the center and plane of rotation:

$$\tilde{x}_H = (\langle \psi_i, n \rangle / \langle \tilde{x}, n \rangle) \tilde{x}, \text{ for any } i \in I$$

$$v = (r - \langle r, n \rangle n) / \|r - \langle r, n \rangle n\|$$

- 2 Project atoms into the $n - v$ -plane and select the next atom:

$$k = \arg \max_{i \in \{1, \dots, n\}} \tan^{-1} \frac{\langle \psi_i - \tilde{x}_H, n \rangle}{\langle \psi_i - \tilde{x}_H, v \rangle}$$

- 3 Compute the new representation and update the biorthogonal system:

$$\{I, A, \tilde{\Psi}^\perp\} = \text{AddAtom}(x, I, A, \psi_k, \tilde{\Psi}^\perp).$$

- 4 Discard any extraneous atoms while:

$$\exists a_i \leq 0, i \in I \text{ do}$$

$$\{I, A, \tilde{\Psi}^\perp\} = \text{SubtractAtom}(x, I, A, \psi_j, \tilde{\Psi}^\perp)$$

- 5 Update the hyperplane parameters:

$$\tilde{x} = \sum_{i \in I} \alpha_i \psi_i$$

$$n = \frac{-\langle \psi_k - \tilde{x}_H, n \rangle v + \langle \psi_k - \tilde{x}_H, v \rangle n}{\|-\langle \psi_k - \tilde{x}_H, n \rangle v + \langle \psi_k - \tilde{x}_H, v \rangle n\|};$$

$$r = x - \tilde{x}$$

3.3 Compressive sampling matching pursuit

CoSaMP is at heart a greedy pursuit algorithm. It is initialized with a trivial signal approximation, which means that the initial residual equals the unknown target signal. During each iteration, CoSaMP performs five major steps, including identification, support merger, estimation, pruning and sample update. These steps are repeated until the halting criterion is triggered.

The following lists the steps of the CoSaMP algorithm.

Algorithm 3. CoSaMP recovery algorithm.

Input:

Sampling matrix Φ , sample vector u and sparsity level K .

Procedure:

Initialize:

$a^0 = 0$; $v = u$; $n = 0$; v is current samples and n is an iteration counter.

Repeat:

- 1 $n = n + 1$, form signal proxy, $y = \Phi^* v$, Φ^* is the Hermitian transpose of Φ ;
- 2 Identify large components:
 $\Omega = \text{supp}(y_n)$;
- 3 Merge support:
 $T = \Omega \cup \text{supp}(a^{n-1})$;
- 4 Signal estimation by least squares: $b|_T = \Phi_T^\dagger u$, $b|_{T^c} = 0$, Φ^\dagger is the pseudo-inverse of Φ such that $\Phi^\dagger = (\Phi^* \Phi)^{-1} \Phi^*$; T^c indicates the compliment of set T ; and $b|_T$ indicates the vector b is restricted by only the elements given in T .
- 5 Prune to obtain next approximation: $a^n = b_k$;
- 6 Update current samples: $v = u - \Phi a^n$; until halting criterion is true.

Output:

A K -sparse approximation a of the target signal.

3.4 Subspace pursuit

The main difference between subspace pursuit (SP) and CoSaMP is the manner of adding new candidates. More precisely, SP only adds K new candidates in each iteration, while CoSaMP adds $2K$, which makes the SP computationally more efficient but the underlying analysis more complex. The following lists the steps of the SP algorithm.

Algorithm 4: CS recovery using SP

Input:

The CS observation y , a measurement matrix $\Phi \in R^{m \times n}$, a signal sparse transform matrix $\Psi \in R^{n \times n}$; sample vector u , sparsity level K .

Procedure:

Initialization:

$T^0 = \{K \text{ indices corresponding to the largest magnitude entries in the vector } \Phi^* y\}$; $y_r^0 = \text{resid}(y, \Phi_{T^0})$.

Iteration: At the l^{th} iteration, go through the following steps:

- 1 $\tilde{T}^l = \tilde{T}^{l-1} \cup \{K \text{ indices corresponding to the largest magnitude entries in the vector } \Phi^* y_r^{l-1}\}$;
- 2 Set $x_p = \Phi_{\tilde{T}^l}^\dagger y$, where $\Phi_{\tilde{T}^l}^\dagger = (\Phi_{\tilde{T}^l}^* \Phi_{\tilde{T}^l})^{-1} \Phi_{\tilde{T}^l}^*$;
- 3 $T^l = \{K \text{ indices corresponding to the largest elements of } x_p\}$;
- 4 $y_r^l = \text{resid}(y, \Phi_{T^l})$;
- 5 If $\|y_r^l\|_2 > \|y_r^{l-1}\|_2$, let $T^l = T^{l-1}$ and quit the iteration.

Output:

The estimated signal \hat{x} , satisfying $\hat{x}_{\{1, 2, \dots, N\} - T^l} = 0$ and $\hat{x}_{T^l} = \Phi_{T^l}^\dagger y$.

4. Reconstruction algorithms for block compressed sensing

4.1 Block compressed sensing

An $N_1 \times N_2$ image is divided into small blocks with a size of $n_1 \times n_2$. Let f_i represent the vectorized signal of the i -th block

through raster scanning, $i = 1, 2 [\dots] n$ and $n = N_1 N_2 / n_1 n_2$. An m -dimensional sampled vector y_b can be obtained through the following linear transformation (Eldar *et al.*, 2010):

$$y_b = \Phi_B f_i \quad (7)$$

where f_i is an $n_1 n_2$ -dimensional vector, Φ_B is an $m \times n_1 n_2$ measurement matrix, $m \ll n_1 n_2$. Note that block CS is memory efficient, as we just need to store an $m \times n_1 n_2$ Gaussian ensemble Φ_B , rather than a full $M \times N_1 N_2$ (i.e. $nm \times n_1 n_2$) one. Small requires less memory in storage and faster implementation, while large offers better reconstruction performance.

The main advantages of block-based CS can be summarized as follows:

- The measurement operator can easily be stored and implemented through a random under-sampled filter bank.
- Block-based measurement is more advantageous for real-time applications, as the encoder does not need to send the sampled data until the whole image is measured.
- Because each block is processed independently the initial solution can be obtained and the reconstruction process is substantially sped up.

4.2 Reconstruction algorithm

It can be seen from the introduction of the CoSaMP algorithm above that the algorithm is initialized with a trivial signal approximation, which means that the initial residual equals the unknown target signal. During each iteration, CoSaMP performs five major steps:

- 1 *Identification*. The algorithm forms a proxy of the residual from the current samples and locates the largest components of the proxy.
- 2 *Support merger*. The set of newly identified components is united with the set of components that appear in the current approximation.
- 3 *Estimation*. The algorithm solves a least squares problem to approximate the target signal on the merged set of components.
- 4 *Pruning*. The algorithm produces a new approximation by retaining only the largest entries in this least squares signal approximation.
- 5 *Sample update*. Finally, the samples are updated so that they reflect the residual, the part of the signal that has not been approximated.

These steps are repeated until the halting criterion is triggered.

In his study, an improved CoSaMP algorithm was used for signal recovery based on block compressing sensing. The detailed algorithm is shown as follows.

Algorithm 5. Block CoSaMP algorithm

Input:

- 1 An image can be divided into some small blocks of a size $n_i \times m_i$, sample rate w ($w \in (0, 1]$);
- 2 The sparsity level k of the block images;
- 3 An $M \times N$ measurement matrix Φ , $N = n^* m$, $M = N^* w$.

Output:

An estimate \hat{x} of an image x

For each block $n_i \times m_i$ image procedure:

Initialization:

- i Transform each $n_i \times m_i$ image block into an $(n_i^* m_i) \times 1$ data vector y ;
- ii $\hat{x}_{-1} = 0$ (\hat{x}_j is the estimate at the j th iteration); and
- iii $r = y$ (the current residual).

Procedure:

Loop until convergence

- i Compute the current error:

$$e^i = \Phi^{*i} r^i$$

- ii Compute the best $2k$ support set of the error (index set):

$$\Omega^i = e_{2k}^i$$

- iii Merge the strongest support sets:

$$T^i = \Omega^i \cup \text{supp}(\hat{x}_{j-1}^i)$$

- iv Perform a least squares signal estimation (Johnson *et al.*, 2012):

$$b^i|_{T^i} = \Phi_{T^i}^{*i} y, \quad b^i|_{T^c} = 0.$$

- v Prune

and compute \hat{x}_j^i for next round:

$$\hat{x}_j^i = b^i|_{T^i}; \quad r^i = y - \Phi^i \hat{x}_j^i.$$

- vi Each

consists of \hat{x}_j^i .

End

5. Experiment

To evaluate the quality of the reconstructed results, the mean square error and peak signal noise ratio (PSNR) can be utilized. They are defined as follows (Huynh-Thu and Ghanbari, 2008);

$$\frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N (\hat{f}(i,j) - f(i,j))^2 \quad (8)$$

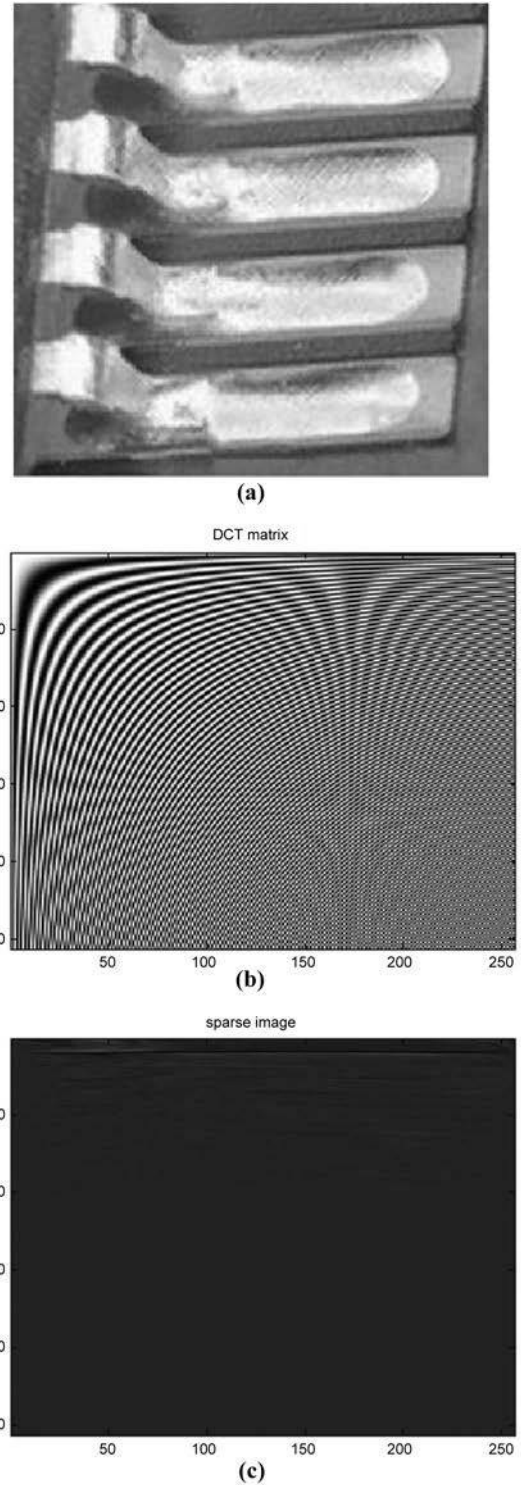
$$\text{PSNR} = 10 \log_{10} \left(\frac{255^2}{\text{MSE}} \right) \quad (9)$$

where M and N are the image dimensions, \hat{f} is the de-noised image and f is the original noiseless image. In this study, the PSNR was used to compare the experimental results.

An original gull-wing lead solder joint image was used as a test image in Figure 1(a) (size 256×256). The sparse transform DCT matrix and sparse image are shown in Figure 1(b,c).

The reconstruction result based on conventional CS with matrix R 's rows $M = 180$ can be seen in Figure 2(b-e), and the reconstruction result based on block CS with sample rate 0.7

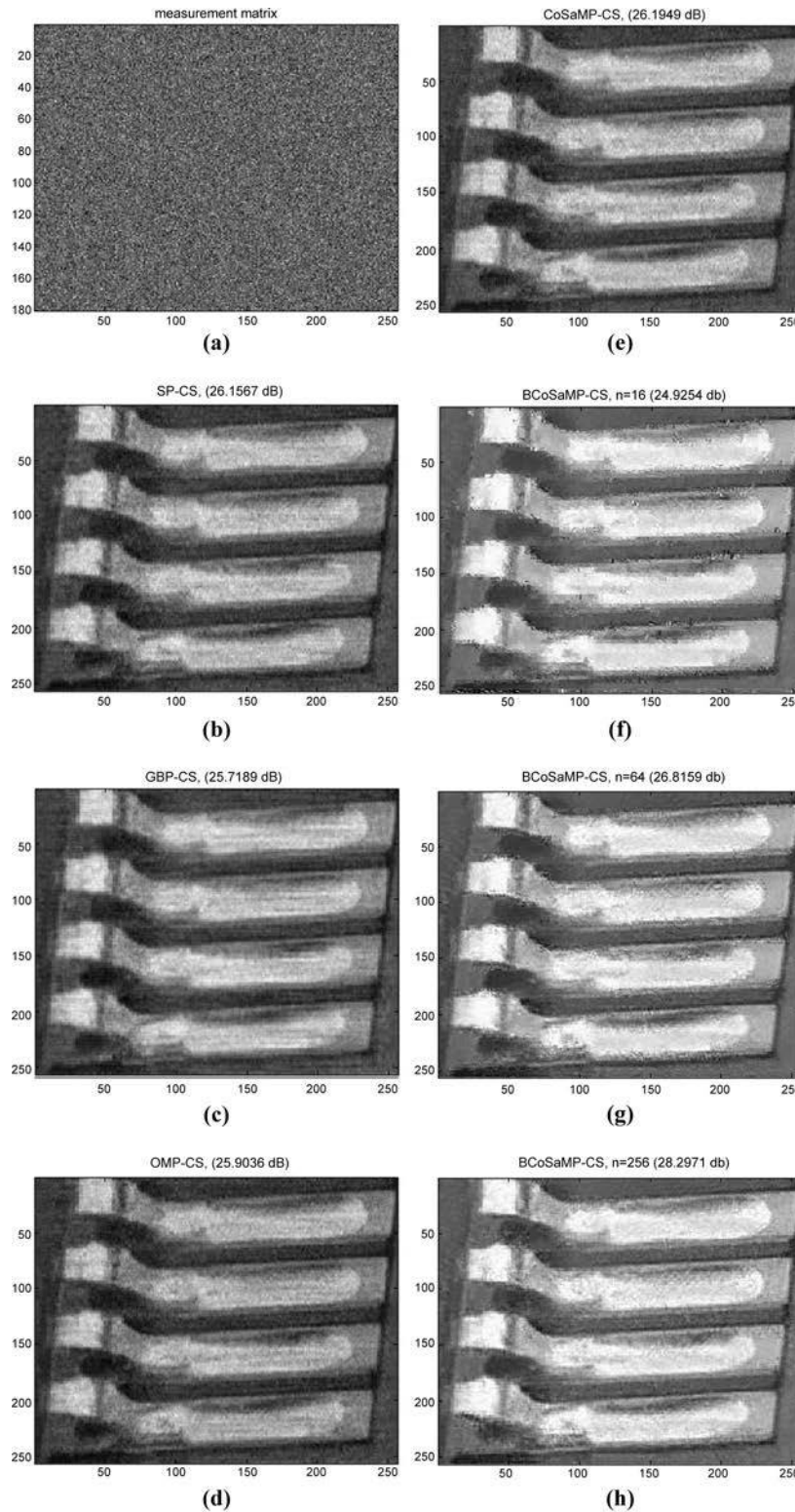
Figure 1 Original image and sparse image



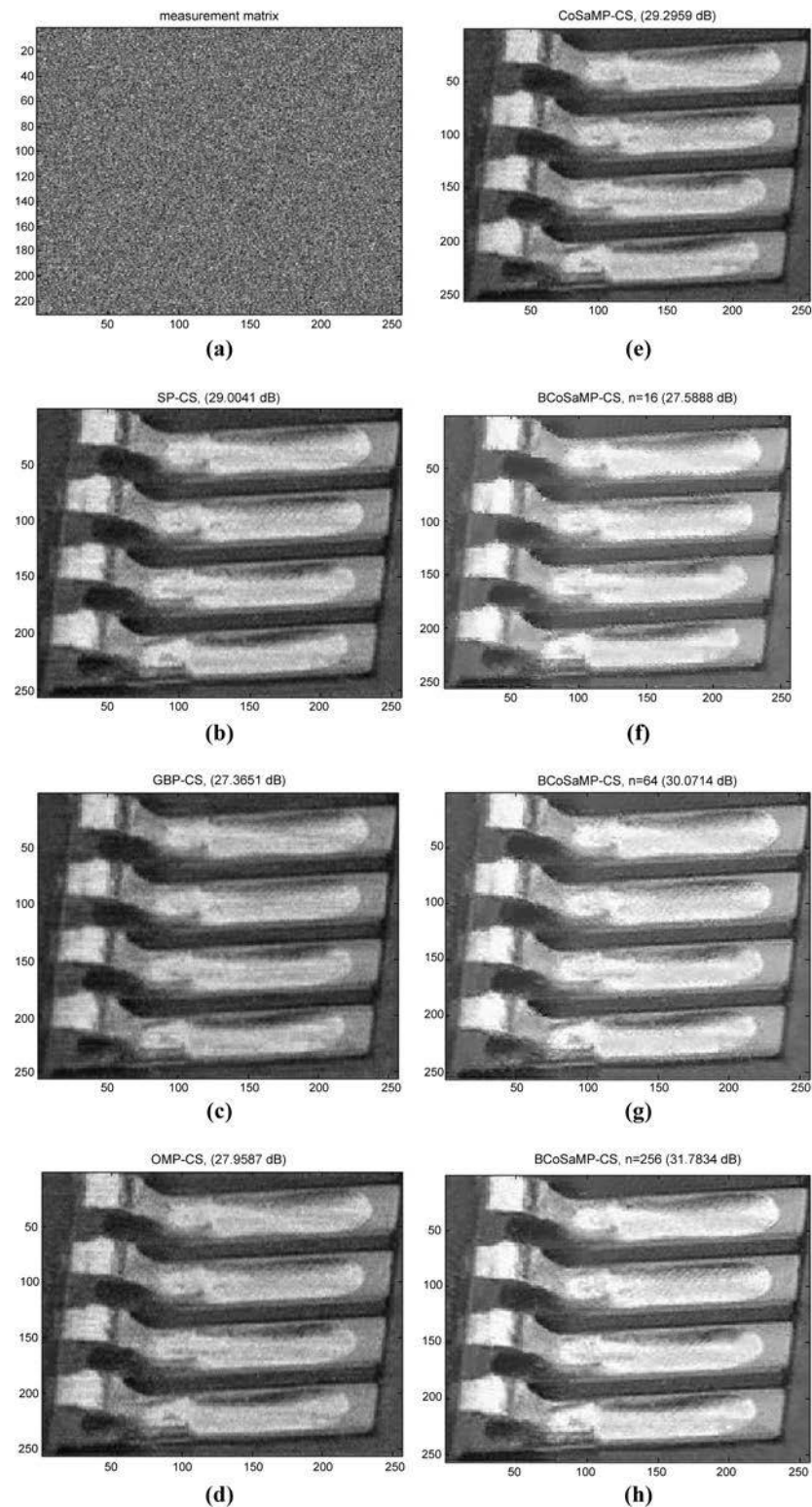
Notes: (a) Original image; (b) Sparse transform DCT matrix; (c) Sparse image

($M/N \approx 0.7$) and block sizes 4×4 , 8×8 and 16×16 can be seen in Figure 2(f-h).

The reconstruction result based on conventional CS with matrix R 's rows $M = 230$ can be seen in Figure 3(b-e), and the

Figure 2 Reconstruction results

Notes: Reconstructed results by using the different methods: (a) measurement matrix in image reconstruction; (b) result by SP algorithm; (c) result by GBP algorithm; (d) result by OMP algorithm; (e) result by CoSaMP algorithm; (f) result by block-CoSaMP algorithm ($N = 16$); (g) result by block-CoSaMP algorithm ($N = 64$); (h) result by block-CoSaMP algorithm ($N = 256$)

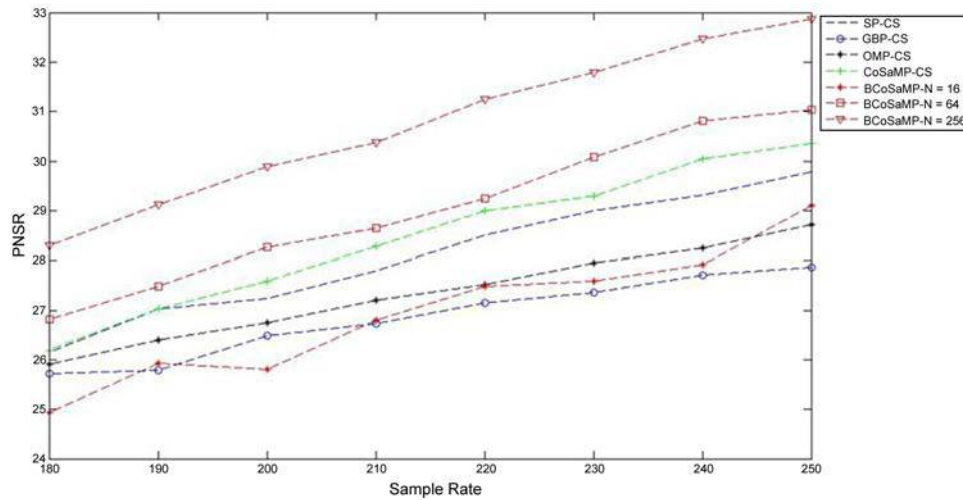
Figure 3 Reconstruction results

Notes: Reconstructed results by using the different methods: (a) measurement matrix in image reconstruction; (b) result by SP algorithm; (c) result by GBP algorithm; (d) result by OMP algorithm; (e) result by CoSaMP algorithm; (f) result by block-CoSaMP algorithm ($N = 16$); (g) result by block-CoSaMP algorithm ($N = 64$); (h) result by block-CoSaMP algorithm ($N = 256$)

Table I. Quantization comparison of reconstructed results

M (M/N)								
Methods	180 (0.70)	190 (0.74)	200 (0.78)	210 (0.82)	220 (0.86)	230 (0.90)	240 (0.94)	250 (0.98)
SP_CS	26.1567	27.0200	27.2385	27.7911	28.5089	29.0041	29.3168	29.7900
GBP_CS	25.7189	25.7793	26.4902	26.7375	27.1526	27.3651	27.7130	27.8708
OMP_CS	25.9036	26.3989	26.7542	27.2056	27.5076	27.9587	28.2425	28.7103
CoSaMP_CS	26.1949	27.0296	27.5797	28.2773	29.0022	29.2959	30.0350	30.3546
Block CoSaMP_CS (N = 16)	24.9254	25.9316	25.8103	26.8031	27.4728	27.5888	27.9073	29.1033
Block CoSaMP_CS (N = 64)	26.8159	27.4830	28.2680	28.6433	29.2425	30.0714	30.8152	31.0331
Block CoSaMP_CS (N = 256)	28.2971	29.1184	29.8828	30.3825	31.2553	31.7834	32.4744	32.8773

Figure 4 Quantization comparisons of reconstructed results with different block size



reconstruction result based on block CS with sample rate 0.9 ($M/N \approx 0.9$) and block size 4×4 , 8×8 and 16×16 can be seen in Figure 3(f-h).

It can be seen by comparing Figure 3(f-h) that the method reported here can obtain better results in PSNR than the results obtained from methods based on conventional CS. The results for varying sample rates are summarized in Table I.

From Table I, it can be seen that the PSNR of the reconstructed results is improved. The new method reported in this paper can obtain better results than those based on conventional CS. The quantization comparison of reconstructed results with different block size can be seen in Figure 4.

As can be seen from Figure 4, the method when block size is 8×8 ($N = 64$) can obtain better results than other traditional methods. During the improved methods, when the block size is 16×16 ($N = 256$), the best results were obtained.

6. Conclusion

This paper has focused on the development of compressing and reconstruction methods for solder joint imagery. There are many algorithms in compressive sampling that have been used to approximate a signal, given a vector of samples. Among them, CoSaMP achieves good performance on PSNR. Solder joint image were divided into some blocks, and an image reconstruction method was proposed based on block compressing sensing with the CoSaMP algorithm. The

performance of the proposed approach has been shown and compared with different block sizes. The main advantages of block CoSaMP are as follows:

- Measurement operator can easily be stored and implemented through a random under-sampled filter bank.
- Block-based measurement is more advantageous for real-time applications.
- The proposed algorithm can be obtained and can achieve the best result on PSNR than other methods.
- The block CoSaMP algorithm when block size is 16×16 can obtain better results than when the block size is 8×8 and 4×4 .

In future studies, the relationship between the size of block and recovery performance will be researched, and the speed of the proposed algorithm will also be considered.

References

- Bayazit, U. (2011), "Adaptive spectral transform for wavelet-based color image compression", *IEEE Transactions on Circuits and Systems for Video Technology*, Vol. 21 No. 7, pp. 983-992.
- Bazerque, J.A. and Giannakis, G.B. (2013), "Nonparametric basis pursuit via sparse kernel-based learning", *IEEE Signal Processing Magazine*, Vol. 30 No. 4, pp. 112-125.

- Benedek, C.S., Krammer, O., Janóczy, M. and Jakab, L. (2013), "Solder Paste Scooping Detection by Multi-Level Visual Inspection of Printed Circuit Boards", *IEEE Transactions on Industrial Electronics*, Vol. 60 No. 6, pp. 2318-2331.
- Bhattacharya, S., Blumensath, T., Mulgrew, B. and Davies, M. (2007), "Fast encoding of synthetic aperture radar raw data using compressed sensing", *2007 IEEE/SP 14th Workshop on Statistical Signal Processing, Madison, WI, 26-29 August*, pp. 448-452.
- Blumensath, T. and Davies, M. (2009), "Iterative hard thresholding for compressive sensing", *Applied and Computational Harmonic Analysis*, Vol. 27 No. 3, pp. 265-274.
- Cai, T.T. and Wang, L. (2011), "Orthogonal matching pursuit for sparse signal recovery with noise", *IEEE Transaction on Information Theory*, Vol. 57 No. 7, pp. 4680-4688.
- Candes, E.J. and Wakin, M.B. (2008), "An introduction to compressive sampling", *IEEE Signal Processing Magazine*, Vol. 25 No. 2, pp. 21-30.
- Davenport, M.A., Needell, D. and Wakin, M.B. (2013), "Signal space CoSaMP for sparse recovery with redundant dictionaries", *IEEE Transactions on Information Theory*, Vol. 9 No. 9, pp. 1-18.
- Donoho, D.L. (2006), "Compressed sensing", *IEEE Transactions on Information Theory*, Vol. 52 No. 4, pp. 1289-1306.
- Donoho, D.L., Elad, M. and Temlyakov, V. (2006), "Stable recovery of sparse overcomplete representations in the presence of noise", *IEEE Transactions on Information Theory*, Vol. 52 No. 1, pp. 6-18.
- Donoho, D.L., Tsaig, Y., Drori, I. and Starck, J.-L. (2012), "Sparse solution of underdetermined systems of linear equations by stagewise orthogonal matching pursuit", *IEEE Transactions on Information Theory*, Vol. 58 No. 2, pp. 1094-1121.
- Eldar, Y.C., Kuppinger, P. and Bolcskei, H. (2010), "Compressed sensing of block-sparse signals: uncertainty relations and efficient recovery", *IEEE Transactions on Signal Processing*, Vol. 58 No. 6, pp. 3042-3054.
- Figueiredo, M.A.T., Nowak, R.D. and Wright, S.J. (2007), "Gradient projection for sparse reconstruction: Application to compressed sensing and other inverse problems", *IEEE J. Selected Topics in Signal Processing: Special Issue on Convex Optimization Methods for Signal Processing*, Vol. 1 No. 4, pp. 586-598.
- Gilbert, A.C., Muthukrishnan, S. and Strauss, M.J. (2005), "Improved time bounds for near-optimal sparse Fourier representation via sampling", in *Proceedings of SPIE Wavelets, XI, San Diego, CA*.
- Gilbert, A., Strauss, M., Tropp, J. and Vershynin, R. (2007), "One sketch for all: fast algorithms for compressed sensing", in *Proceeding 2007 39th ACM Symposium Theory of Computing, San Diego, June*.
- Hongwei, X., Xianmin, Z., Yongcong, K. and Gaofei, O. (2011), "Solder joint inspection method for chip component using improved AdaBoost and decision tree", *IEEE Transaction on components, Packaging and Manufacturing Technology*, Vol. 1 No. 12, pp. 218-227.
- Huynh-Thu, Q. and Ghanbari, M. (2008), "Scope of validity of PSNR in image/video quality assessment", *Electronics Letters*, Vol. 44 No. 13, pp. 800-801.
- Iwen, M. (2008), "A deterministic sub-linear time sparse Fourier algorithm via non-adaptive compressed sensing methods", *2008 in Proceeding ACM-SIAM Symposium on Discrete Algorithms (SODA), San Francisco, CA, January*, pp. 20-29.
- Janoczki, M., Borbiri, A., Nagy, S. and Jakab, L. (2010), "Illumination optimization for quasi-tombstone detection", *Micro and Nanosystems*, Vol. 2 No. 3, pp. 149-162.
- Johnson, K.M., Block, W.F., Reeder, S.B. and Samsonov, A. (2012), "Improved least squares MR image reconstruction using estimates of k-Space data consistency", *Magnetic Resonance in Medicine*, Vol. 67 No. 6, pp. 1600-1608.
- Jørgensen, J.H., Sidky, E.Y. and Pan, X. (2012), "Quantifying admissible undersampling for sparsity-exploiting iterative image reconstruction in X-ray CT", *IEEE Transactions on Medical Imaging*, Vol. 32 No. 2, pp. 460-473.
- Karami, A., Yazdi, M. and Mercier, G. (2012), "Compression of hyperspectral images using discrete wavelet transform and tucker decomposition", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 5 No. 2, pp. 444-450.
- Lustig, M., Donoho, D. and Pauly, J.M. (2007), "Sparse MRI: the application of compressed sensing for rapid MR imaging", *Magnetic Resonance in Medicine*, Vol. 58 No. 6, pp. 1182-1195.
- Needell, D. and Tropp, J.A. (2010), "CoSaMP: iterative signal recovery from incomplete and inaccurate samples", *Communications of the ACM*, Vol. 53 No. 12, pp. 93-100.
- Needell, D. and Vershynin, R. (2009), "Uniform uncertainty principle and signal recovery via regularized orthogonal matching pursuit", *Foundations of Computational Mathematics*, Vol. 9 No. 3, pp. 317-334.
- Tropp, J.A. and Gilbert, A.C. (2007), "Signal recovery from random measurements via orthogonal matching pursuit", *IEEE Transaction on Information Theory*, Vol. 53 No. 12, pp. 4655-4666.
- Vasanawala, S.S., Alley, M.T., Hargreaves, B.A., Barth, R.A., Pauly, J.M. and Lustig, M. (2010), "Improved pediatric MR imaging with compressed sensing", *Radiology*, Vol. 256 No. 2, pp. 607-616.
- Wu, F. and Zhang, X. (2011), "Inspection of pseudo solders for lead-free solder joints in PCBs", *Optics and Precision Engineering*, Vol. 19 No. 3, pp. 697-702.
- Wu, H., Zhang, X., Xie, H., Kuang, Y. and Ouyang, G. (2013), "Classification of solder joint using feature selection based on bayes and support vector machine", *IEEE Transactions on components Packaging and Manufacturing Technology*, Vol. 3 No. 3, pp. 516-522.
- Xiong, G., Lu, J. and Wu, S. (2012), "New Automatic Optical Inspection System for PCB", *Proceedings of the 2012 International Conference on Electronics, Communications and Control*, pp. 1270-1273.

About the authors

Huihuang Zhao received a PhD degree from the School of Mechano-Electronic Engineering, Xidian University, Xi'an,

China, in 2010. He is currently Assistant Professor in the Computer Science Department, Hengyang Normal University. His research interests include computer vision and surface mount technology. Huihuang Zhao is the corresponding author and can be contacted at: happyday.huihuang@gmail.com

Wang Yaonan received a PhD degree from Hunan University in 1994. He is Professor and Doctoral Supervisor in Hunan University and is the Dean of College of Electrical and Information Engineering. His research interests include intelligent control and pattern recognition.

Zhijun Qiao received a PhD degree from Fudan University in 1997. He is Professor of Mathematics in the Department of Mathematics, University of Texas-Pan American. His research interests include integrable systems, solitons, Image PDEs and analysis, mathematical model, compressive sensing and radar image reconstructions.

Bin Fu received a PhD degree from Yale University in 1998. He is Professor of Computer Science in the Department of Computer Science, University of Texas-Pan American. His research interests include bioinformatics algorithms and computational complexity theory.

This article has been cited by:

1. ZhaoHuihuang Huihuang Zhao Huihuang Zhao received his PhD degree from the School of Mechano-Electronic Engineering, Xidian University, China, in 2010. He is currently an Associate Professor in the Computer Science Department, Hengyang Normal University. His research interests include computer vision and surface mount technology. ChenJianzhen Jianzhen Chen Jianzhen Chen received his PhD degree in 2010. He is the Vice Dean of Computer Science Department and currently a Professor in the Computer Science Department, Hengyang Normal University. His research interests include intelligent control and pattern recognition, GPU computing. XuShibiao Shibiao Xu Shibiao Xu received the BS degree in information engineering from the Beijing University of Posts and Telecommunications, Beijing, China, in 2009 and the PhD degree in computer science from the Institute of Automation, Chinese Academy of Sciences, Beijing, China, in 2014. He is currently a Postdoctoral Researcher with the State Key Laboratory of Virtual Reality Technology and Systems, Beihang University, Beijing. His current research interests include computer vision and image-based three-dimensional scene reconstruction and understanding. WangYing Ying Wang Ying Wang received her Master's degree from the School of Computer Science, Hunan University, China, in 2012. She is currently an Associate Professor in the Computer Science Department, Hengyang Normal University. Her research interests include image processing. QiaoZhijun Zhijun Qiao Zhijun Qiao received his PhD degree from Fudan University in 1997. He is a Professor of mathematics in the department of Mathematics, University of Texas-Pan American. His research interests include integrable systems, solitons, image PDEs and analysis, mathematical model, compressive sensing and radar image reconstructions. Department of Computer Science, HengYang Normal University, HengYang, China National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, Beijing, China Department of Computer Science, HengYang Normal University, HengYang, China Department of Mathematics, University of Texas-Pan American, Edinburg, TX, USA . 2016. Compressive sensing for noisy solder joint imagery based on convex optimization. *Soldering & Surface Mount Technology* **28**:2, 114-122. [[Abstract](#)] [[Full Text](#)] [[PDF](#)]