Compressive Sensing SAR Image Reconstruction Based on Bayesian Framework and Evolutionary Computation

Jiao Wu, Student Member, IEEE, Fang Liu, Senior Member, IEEE, L. C. Jiao, Senior Member, IEEE, and Xiaodong Wang

Abstract—Compressive sensing (CS) is a theory that one may achieve an exact signal reconstruction from sufficient CS measurements taken from a sparse signal. However, in practical applications, the transform coefficients of SAR images usually have weak sparsity. Exactly reconstructing these images is very challenging. A new Bayesian evolutionary pursuit algorithm (BEPA) is proposed in this paper. A signal is represented as the sum of a main signal and some residual signals, and the generalized Gaussian distribution (GGD) is employed as the prior of the main signal and the residual signals. BEPA decomposes the residual iteratively and estimates the maximum a posteriori of the main signal and the residual signals by solving a sequence of subproblems to achieve the approximate CS reconstruction of the signal. Under the assumption of GGD with the parameter \(0 < p < 1\), the evolutionary algorithm (EA) is introduced to CS reconstruction for the first time. The better reconstruction performance can be achieved by searching the global optimal solutions of subproblems with EA. Numerical experiments demonstrate that the important features of SAR images (e.g., the point and line targets) can be well preserved by our algorithm, and the superior reconstruction performance can be obtained at the same time.

Index Terms—Compressive sensing (CS), evolutionary algorithm, maximum a posteriori estimation, pursuit algorithm.

I. INTRODUCTION

ASSUME that the object of interest \( \mathbf{x} \in \mathbb{R}^M \) is a \( m \)-sparsity signal. With the sensing matrix \( \Phi \in \mathbb{R}^{K_{CS} \times M} \) \((K_{CS} \ll M)\), the measurements \( \mathbf{y} = \Phi \mathbf{x} \in \mathbb{R}^{K_{CS}} \) are taken by projecting \( \mathbf{x} \) to a \( K_{CS} \)-dimensional space. According to the theory of compressive sensing (CS) [1], [2], it is really only necessary to take \( K_{CS} = O(m \log(M/m)) \) measurements to get an accurate reconstruction of \( \mathbf{x} \) by solving a convex program

\[
\min \| \mathbf{x} \|_1 \quad \text{s.t.} \quad \Phi \mathbf{x} = \mathbf{y} \tag{1}
\]

where \( M \) is the length of \( \mathbf{x} \). It is a basic framework of many recent CS reconstruction algorithms (see [3]–[8], among many others).

For the sparse signal, an accurate reconstruction can be obtained with enough CS measurements; however, the signal applied in practice usually has not strong sparsity, for example, synthetic aperture radar (SAR) images, which are the complicated images widely applied in military and civil utilization. Because of existing miscellaneous objective, more singular information and speckle noise, the transform coefficients of SAR images are not exactly sparse, but are compressible. A large number of CS measurements are necessary to achieve the high-quality reconstruction of SAR images. To trade off the recovered accuracy and sample rate, the number of CS measurements \( K \) used in practice is usually less or far less than the requirement \( K_{CS} \) of CS theory. Ensuring the effectiveness of the recovered algorithm and achieving good reconstruction quality with the smaller value of \( K \) is one of the challenging problems of successfully applying CS theory into practice.

In this paper, a new pursuit algorithm based on Bayesian framework and evolutionary computation, named Bayesian evolutionary pursuit algorithm (BEPA), is proposed for the CS reconstruction problem of SAR images with weak sparsity. A signal is represented as the sum of a main signal and some residual signals. Similar to matching pursuit (MP) [4], BEPA decomposes the residual iteratively and estimates the maximum a posteriori (MAP) of the main signal and the residual signals by solving a sequence of subproblems to achieve the approximate CS reconstruction of the signal. Here, a multiscale compressive sampling scheme [9] is utilized to observe projection of the wavelet coefficients of SAR images, and the wavelet coefficients are estimated based on a given number of CS measurements. It is well known that a widely used model to depict the statistical property of the wavelet coefficients is the generalized Gaussian distribution (GGD) [10] (or the generalized Laplacian distribution (GLD) [11], [12]). For BEPA, we assume that the prior of the main signal is GGD with the parameter \(0 < p < 1\), and the prior of the residual signals is GGD with \( p = 2\).

The contributions of this paper are as follows. For \(0 < p < 1\), estimating the MAP of the main signal is a nonlinear multimodal
function optimization, it is not analytically solved. Considering
the problem of a local optimum caused by traditional optimal
methods, evolutionary computation is adopted to perform global
searching and therefore achieve better reconstruction quality
of images. It is the first time integrating evolutionary computation
with CS reconstruction. Moreover, a Bayesian pursuit algorithm
(BPA) is also developed for comparison. Based on the assump-
tion of GGD with $p = 1$, a common optimal method is used in
BPA to estimate the MAP of the main signal, thereby giving
BPA a fast recovered speed.

SAR images are complicated images. We desire not only to
obtain smaller reconstruction error, but also, more importantly,
to preserve as many important features of source SAR images
as possible in reconstructed images. The numerical experiments
validate the preservation ability of BEPA for the important
features of SAR images. The point and line targets of SAR images
can be well maintained, and a superior reconstruction perform-
ance can be obtained as a whole at the same time. Experiments
demonstrate that BEPA is an available CS reconstruction algo-
rithm for SAR images with weak sparsity.

This paper is outlined as follows. BEPA is proposed in
Section II, and the basic idea and implementation method are
introduced. BPA is derived for comparison in Section III. In
Section IV, the performance of BEPA is verified in the experi-
ments of SAR images, with comparisons to many of the state-of-
the-art CS algorithms. Conclusions are discussed in Section V.
The Appendix presents the sensitivity analysis of parameters.

II. BAYESIAN EVOLUTIONARY PURSUIT ALGORITHM

The main idea of BEPA is that a signal $x$ is represented as the
sum of a main signal $x^0$ and some residual signals $x^1, x^2, \ldots,$
that is, $x = x^0 + \sum_{n=1}^{\infty} x^n$. Similar to an MP algorithm, we
decompose the residual vector $r^j$ iteratively and respectively
obtain the estimations of the main signal and the residual signals
$\hat{x}^0, \hat{x}^1, \hat{x}^2, \ldots$ by solving a sequence of subproblems. Then, the
approximate CS reconstruction of $x$ is achieved by $\hat{x} \approx \hat{x}^0 + \sum_{n=1}^{N} \hat{x}^n$.

A. Procedure of BEPA

BEPA includes two stages. The first stage is to reconstruct the
main signal, and the second stage is to reconstruct the residual
signals. BEPA operates in $N + 1$ steps. The concrete implemen-
tation steps of these two stages are as follows:

1) Reconstruction of the Main Signal: BEPA starts with
initial residual $r^0 = y$. First, a vector of residual corre-
lations $u = \Phi^T r^0$ is computed. Sorting $\{(u_k)\}_{k=1}^M$ in descending sort
order, let $S = \{s_1, s_2, \ldots, s_M\}$ be the corresponding index set, such that $|u_{s_1}| > \cdots > |u_{s_M}|$. Then, we know that
$|u_{s_1}|$ with the large value corresponds to the obviously nonzero entries of $x$. According to the order of the index set $S$, the
elements of $x$ are estimated successively by solving a sequence of
subproblems. Let $r^{m-1}$ be an updated residual vector after esti-
matting the $s_m$-th element of $x$. We solve a subproblem with
respect to the $s_m$-th element of $x$ to obtain its estimated value
$\hat{x}_{s_m}^0$. Then, the updated residual is

$$r^m = r^{m-1} - \phi_{s_m} \hat{x}_{s_m}^0$$

where $\phi_{s_m}$ is a column vector of $\Phi$ corresponding to the $s_m$-th
element of $x$. The procedure mentioned above is repeated $M_0$
times to obtain $M_0$ estimated elements of $x$, and the rest of the
$M - M_0$ elements of $x$ are equal to zero, where $M_0 \leq M$,
the smaller value of $M_0$ can be selected according to the concrete
problems. Then, an approximation $\hat{x}^0$ of $x$ is obtained. $\hat{x}^0$ is just
the estimation of the main signal. Set $r^1 = r^{M_0}$.

2) Reconstruction of the Residual Signals: Starting with the
residual $r^1$, the reconstruction of the residual signals per-
forms $N$ times iteratively. Let $r^n$ be the residual at the $n$-th
iteration. Similar to the reconstruction procedure of the main
signal, letting $r^0 = r^n$, we estimate $M_0$ elements of the
residual signal $x^n$ and let the rest of $M - M_0$ elements equal
to zeros to obtain the approximation $\hat{x}^n$ by solving the subprob-
lems in the order of the index set $S = \{s_1, \ldots, s_M\}$, which is
designed by sorting $\{(u_k)\}_{k=1}^M$ in descending sort order. Upd-
tating the residual to $r^{n+1}$, we check a stopping condition
and, if it is not yet time to stop, we set $n = n + 1$ and go to
the next reconstruction procedure of the residual signal. If it is
time to stop, $\hat{x} = \hat{x}^0 + \sum_{n=1}^{N} \hat{x}^n$ is computed as the final
approximated reconstruction of $x$. Note that there are two natural
approaches to halting the algorithm. One is to stop after a fixed
reconstructed times of the main and residual signals. The other
is to use a $c_0$-insensitive criterion, that is, the mean square error
of the current residual $r^{n+1}$ is less than a positive constant $c_0$.
In this work, we concentrate on the method that uses a fixed
number of reconstructions.

The differences between the above reconstruction procedures
of two stages in BEPA are the methods of solving the subprob-
lems. From the view of Bayesian learning, the basic assumption
and solving method of subproblems in BEPA are given in the
following subsections.

B. Basic Assumptions of BEPA

Solving subproblems of BEPA can be considered as the
problem of solving the following model:

$$r = \phi x + \varepsilon$$

where $x$ is a certain element of the main signal or the residual
signal, $\phi$ is a column vector of the sensing matrix $\Phi$ cor-
responding to $x$, $r$ is a residual vector, and $\varepsilon$ is a Gaussian noise
with precision $\beta^{-1}\mathbf{1}$. We assume that the residual $r$ follows
a Gaussian distribution

$$p(r|x, \beta) = N(r|\phi x, \beta^{-1}\mathbf{1})$$

where $\mathbf{1} = (1, \ldots, 1)^T$. A generalized Gaussian distribution
shown in (5) is introduced to depict the prior distribution of
the main signal and the residual signal

$$p(x|\lambda) = \frac{\lambda^p}{2\Gamma(1/p)} \exp\{-\lambda \cdot |x|^p\}$$

where $p$ is the shape parameter, $\lambda$ is scale parameter, and $\Gamma(\cdot)$
is a Gamma function. For the main signal, we take $0 < p <
1$. For the residual signal, we take $p = 2$, that is, a Gaussian
distribution with zero mean and precision $\lambda$. The parameter $\lambda$
is also known as the hyper-parameter of (5).
C. Solving Subproblems

There are two popular methods can be utilized to solve model (3) based on GGD prior: one is MAP estimation of $x$. MAP transforms the problem (3) to a single variable optimization. The other is Bayesian inference [13] of $x$. Bayesian inference estimates the posterior of $x$ by learning the hyper-parameter. In this paper, we estimate the MAP of $x$.

Given the fixed value of hyper-parameter $\lambda$, the MAP of $x$ can be estimated by maximizing the log-posterior of $x$ as

$$\hat{x}_{\text{MAP}} = \arg \max_x \{ f(x) = \log p(x|\mathbf{r}) \}$$

$$= \arg \max_x \{ f(x) = \log p(x) + \log p(\mathbf{r}|x) + \log p(\lambda) \}.$$ \hspace{1cm} (6)

Substituting (4) and (5) into (6), we have

$$\hat{x}_{\text{MAP}} = \arg \max_x \left\{ f(x) = -\frac{\beta}{2} \| \mathbf{r} - \phi x \|^2 - \lambda P^2 + \text{const} \right\}.$$ \hspace{1cm} (7)

Letting $\hat{\lambda} = 2\lambda P/\beta$, the optimization problem of estimating the MAP of $x$ can be simplified into

$$\min_x \left\{ f(x) = \| \mathbf{r} - \phi x \|^2 + \hat{\lambda} P \right\}.$$ \hspace{1cm} (8)

1) Evolutionary Algorithm Inspired Solving Subproblems of the Main Signal Reconstruction: For the main signal, we have assumed $0 < p < 1$. The objective function of (8) is a nonlinear multimodal function, and it is not analytically solved. Considering the problem of local optimum caused by traditional optimal methods, we adopt evolutionary computation to perform global searching. The flow of evolutionary algorithm (EA) is shown in Table 1.

The objective function of (8) is selected as the fitness function $f(x)$ of EA. The population evolutionary is realized by selection and mutation operation during the evolutionary process. And elitism preservation is used to improve the convergence accuracy and speed of EA. Selection probability is defined according to the fitness of individuals. Letting $f_i$ be the fitness of the $i$th individual, selection probability $p_{sl}$ of the $i$th individual is defined as

$$p_{sl} = \frac{\exp(-\frac{f_i}{L})}{\sum_{k=1}^{L} \exp(-\frac{f_k}{L})}, \quad l = 1, \ldots, L.$$ \hspace{1cm} (9)

where $\frac{f_i}{L} = f_i/(\sum_{k=1}^{L} \frac{f_k}{L})^{1/2}, L$ is the population size. The Gaussian mutation is adopted in EA. For the $l$th individual $x_l$, mutation refers to generate a new individual $x'_l$ as follows:

$$x'_l = x_l + \eta_l, \quad l = 1, \ldots, L.$$ \hspace{1cm} (10)

where $\eta_l$ is a random number following the Gaussian distribution $N(0, \sigma^2)$.

2) Solving Subproblems of the Residual Signal Reconstruction: For the residual signals, we have $p = 2$, and the optimization problem (8) takes the form

$$\min_x \left\{ f(x) = \| \mathbf{r} - \phi x \|^2 + \hat{\lambda} x^2 \right\}.$$ \hspace{1cm} (11)

It is quite easy to estimate the MAP of $x$ as

$$\hat{x}_{\text{MAP}} = \frac{\mathbf{r}^T \phi}{\phi^T \phi + \hat{\lambda}}.$$ \hspace{1cm} (12)

III. BAYESIAN PURSUIT ALGORITHM

The GGD with the parameter $p = 1$ is also used as the prior of the main signal for comparison. In this case, (5) is the Laplace distribution, and the optimization problem (8) takes the form

$$\min_x \left\{ f(x) = \| \mathbf{r} - \phi x \|^2 + \hat{\lambda} |x| \right\}.$$ \hspace{1cm} (13)

The optimal solution of (13) can be analytically solved with the common optimization method

$$\hat{x}_{\text{MAP}} = \min \left\{ \frac{2\mathbf{r}^T \phi - \hat{\lambda}}{2\phi^T \phi}, \frac{2\mathbf{r}^T \phi + \hat{\lambda}}{2\phi^T \phi} \right\}.$$ \hspace{1cm} (14)

The obtained pursuit algorithm is named the Bayesian pursuit algorithm (BPA).

IV. EXPERIMENT RESULTS

Here, the CS reconstruction experiments of SAR images are considered to verify the validity of our algorithm. Seven images with the size of $256 \times 256$ are tested: the first image is a...
Fig. 1. Performance comparisons for CS reconstruction of seven SAR images using different algorithms with varying sample rates. Reconstruction error as a function of CS sample rate are shown in the left column; the right column shows the associated CPU time, respectively. The reconstruction results of BEPA are the average result of 20 independent trails. (a) Comparison of reconstruction accuracy and CPU time for Stanwick. (b) Comparison of reconstruction accuracy and CPU time for Piperiver. (c) Comparison of reconstruction accuracy and CPU time for Chinalake. (d) Comparison of reconstruction accuracy and CPU time for Russland. (e) Comparison of reconstruction accuracy and CPU time for Yellowriver-sl. (f) Comparison of reconstruction accuracy and CPU time for Yellowriver-ml. (g) Comparison of reconstruction accuracy and CPU time for Palsar.

The scene is the rural area surrounding the town of Stanwick in Bedfordshire in southeast England, and it contains many urban and natural features that typically appear in high-resolution airborne SAR imagery. The second is a Ku-band SAR image (relevant to the pipeline over the Rio Grande river near Albuquerque, New Mexico) with 1-m resolution. The third is a Ku-band SAR image (relevant to the China Lake Airport, California) with 3-m resolution. The fourth is a part of the first TerraSAR-X image (relevant to the south Russian Steppes) with 15-m resolution. The fifth and sixth are two C-band RadarSAT-2 SAR images (relevant to the Yellow River mouth area, Shandong, China) with 8-m resolution. The former is single-look, and the latter is four-look. The last one is an L-band PALSAR image (relevant to Fujiyama, Japan) with 10-m resolution. Abundant

The sensing matrix of CS theory. In this paper, we introduce an orthogonal random sensing matrix and use it for signal reconstruction. For the main signal reconstruction, we can see that some CS reconstruction algorithms are invalid and, far from improving the reconstruction accuracy, may even lead to worse results. This requires that the reconstruction algorithms have the ability to reconstruct the important features of SAR images with less CS measurements.

When the multiscale CS scheme is used to sample the wavelet coefficients of SAR images, the increased sample rate is mainly affected by the sample rate of the highest scale \( j = 8 \). A great number of nonzero coefficients exist in this highest scale, and reflect the important features (i.e., point and line targets, edge and texture) of SAR images. Relative to the coefficients in the low scales, the magnitude of the coefficients in the high scales is usually small. Letting these coefficients equal to zeros to decrease the sample rate will induce the loss of the important features of images. Thus, we have to sample the coefficients in the high scales. Therefore, the problem of the greatly increased sample rate appears. This requires that the reconstruction algorithms have the ability to reconstruct the important features of SAR images with less CS measurements.

To trade off the recovered accuracy and sample rate, the number of CS measurements \( K \) used in practice is usually less or far less than the requirement \( K_{CS} \) of CS theory. In the case of small \( K \), we can see that some CS reconstruction algorithms are invalid and, far from improving the reconstruction quality, the reconstruction accuracy decreases. In the following experiments, the performance of BEPA is studied by reconstructing the aforementioned seven SAR images from CS with varying sample rates. The linear reconstruction result, that is, the coefficients of the highest scale \( j = 8 \) are set to zeros, and the reconstruction results of BP, MP, StOMP (with CFAR thresholding), BCS, LARS/LASSO and BPA, BEPA are compared.

The wavelet coefficients in the highest scale \( j = 8 \) are decomposed into six layers, that is, \( \mathbf{x} \approx \mathbf{x}^0 + \sum_{n=1}^{6} \mathbf{x}^n \). The times of solving subproblems for the reconstruction of the main signal and the residual signals are taken \( M_0 = K \). For the residual signals, let \( p = 2 \) and \( \lambda = 1.5 \). For the main signal reconstruction of BPA, the value range of \( \lambda \) is 0.01–0.3. From the results of experiments, we find that the reconstruction accuracy of BEPA

![Fig. 2. Comparisons of the BPA and BEPA reconstruction images with 30% CS sample rate in scale \( j = 8 \). Left, middle, right columns are original images and reconstructed images from 31,120 measurements with BPA and BEPA, respectively. The reconstruction results of BEPA are the best result of 20 independent trails (similarly hereinafter).](image-url)
on linear reconstruction. From the recovered time shown in the right column of Fig. 1, BPA and StOMP(CFAR) have the fastest recovered speed. The speed of BPA is seldom affected by the increased sample rates. StOMP(CFAR) has the fast speed in the case of low sample rates. However, its speed decreases as the sample rate increases. Compared with BPA, BEPA slows down due to the global search of EA, but it is faster than MP, BCS, and LARS/LASSO with sample rates exceeding 35%, and faster than BP with sample rate exceeding 60%.

Take the case of 30% sample rate in scale \( j = 8 \) (i.e., total number of CS measurements \( K = 31200 \), total sample rate is about equal to 47.48%), the BPA and BEPA reconstruction images of seven test images are shown in the middle and right columns of Fig. 2, respectively. The original images are shown in the left column. We can see that fewer scratch marks are produced by BEPA than BPA. Fig. 3 depicts the Chinalake and Russland images of BEPA recovered from the four CS sample rates in scale \( j = 8 \) that are 10%, 30%, 50%, and 70%. The first and third rows of Fig. 3 are the reconstructed Chinalake and Russland images, respectively. The second and fourth rows give the associated negative differential charts between the original image and reconstructed images to display the changes of reconstruction error with increasing CS sample rate intuitively. Obviously, the artifacts and errors of the reconstructed images gradually decrease with increasing sample rate. In addition, the preservation of the point and line targets of original SAR images also has a great improvement.

V. CONCLUSION

We have developed a new pursuit algorithm, BEPA, for the CS reconstruction of SAR images by integrating EA under Bayesian framework. A signal is represented as the sum of a main signal and some residual signals, and the different prior distributions are employed to the main signal and the residual signals. BEPA decomposes the residual iteratively, and estimates the MAP of the main signal and the residual signals by solving a sequence of the subproblems, so as to achieve the approximate CS reconstruction of the signal. Under the assumption of GGD with \( 0 < p < 1 \) for the main signal, BEPA produces a superior reconstruction quality by searching the global optimal solutions of the subproblems with EA. We have tested the efficiency of BEPA for CS reconstruction of SAR images. Numerical experiments demonstrate that BEPA has a high reconstruction performance. This shows that BEPA is an available CS reconstruction algorithm for SAR images with weak sparsity.

The aforementioned results are achieved based on the independence assumption of the wavelet coefficients. However, the wavelet coefficients of images are usually statistically dependent. It is expected that the results can be further improved if the clustering of wavelet coefficients inside each subband is exploited for CS reconstruction. This is worth studying and exploring in future work.

APPENDIX

ANALYSIS OF PARAMETERS SENSITIVITY

There are several key parameters that affect the performance of BEPA and BPA. The detail analysis of parameters sensitivity is discussed in the following subsections.
Fig. 4. Changes of the parameter $\lambda$ for solving the subproblems of the main signal using BEPA and BPA with varying sample rates. The left plot shows the changes of $\lambda$ as a function of CS sample rate for seven test images in the case of BEPA. The case of BPA is showed in the right plot.

Fig. 5. Reconstruction errors of BEPA for seven test images as a function of $\lambda$ with varying CS sample rates. (a) Stawick. (b) Piperiver. (c) Chinalake. (d) Russland. (e) Yellowriver-sl. (f) Yellowriver-ml. (g) Palsar.

Fig. 6. Example variation of the performance of BEPA with parameter $p$. (a) Reconstruction errors as a function of $p$. (b) Associated CPU time.

A. Sensitivity Analysis of $\tilde{\lambda}$

For the MAP estimation to the solution of the subproblems that arise in BEPA and BPA, this requires different fixed values of $\lambda$ for the reconstruction of the main signal and the residual signals, respectively. In the experiments, we take $\lambda = 1.5$ to solve the subproblems of the residual signals. The small fluctuation of $\tilde{\lambda}$ for the residual signals has almost no effect on the reconstruction accuracy for all types of images used in this paper. Therefore, for each image, giving $\lambda = 1.5$ for the residual signals, we try the varying $\lambda$ over a wide range for the main signal.

Fig. 4 shows the value range of $\lambda$ for solving the subproblems of the main signal using BEPA and BPA with varying sample rates. The left plot shows the changes of $\lambda$ as a function of CS sample rate for seven test images in the case of BEPA. The right plot shows the changes of $\lambda$ in the case of BPA. In the experiments, for each image, we test the reconstruction accuracy with a wide range of $\lambda$ (0.01–1.5) in varying sample rates. The value of $\lambda$ in a fixed sample rate shown in Fig. 4 corresponds to the best accuracy. From Fig. 4 we can see that the value of $\lambda$ tends to decrease for increasing sample rate and decreasing the intensity of speckle noise. The reconstruction errors as a function of $\lambda$ with varying CS sample rates for seven test images are shown in Fig. 5(a)–(g). These results also show the aforementioned variation trends of $\lambda$ for varying images and CS sample rates. In addition, the small fluctuation of $\lambda$ around the best values given in Fig. 4 has only a small effect on the reconstruction accuracy.

B. Sensitivity Analysis of $p$

Next, given a fixed CS sample rate (30%), we take the Russland image as an example to show how sensitive the performance of BEPA is to the change of $p$. Fig. 6 shows the variation of the reconstruction performance of BEPA with varying value of $p$. We can see that the reconstruction error slightly increases and the recovered speed of BEPA slows down for decreasing value of $p$. Thus, $p = 0.9$ is chosen for our experiments.

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REFERENCES


Jiao Wu (S’09) received the B.S. degree and M.S. degree in applied mathematics from Shaanxi Normal University, Xi’an, China, in 1999 and 2002, respectively. She is currently working toward the Ph.D. degree in computer application technology at the School of Computer Science and Technology, Xidian University and the Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education of China, Xi’an, China.

Her research interests include image processing, machine learning, and statistics learning theory and algorithms.

Fang Liu (M’07–SM’07) received the B.S. degree in computer science and technology from Xi’an Jiaotong University, Xi’an, China, in 1984, and the M.S. degree in computer science and technology from Xidian University, Xi’an, in 1995.

Currently, she is a Professor with the School of Computer Science, Xidian University, Xi’an, China. She is the author or coauthor of five books and more than 80 papers in journals and conferences. Her research interests include signal and image processing, synthetic aperture radar image processing, multiscale geometry analysis, learning theory and algorithms, optimization problems, and data mining.

L. C. Jiao (SM’89) received the B.S. degree from Shanghai Jiaotong University, Shanghai, China, in 1982, and the M.S. and Ph.D. degrees from Xi’an Jiaotong University, Xi’an, China, in 1984 and 1990, respectively.

He is currently a Distinguished Professor with the School of Electronic Engineering, Xidian University, Xi’an, China. His research interests include signal and image processing, natural computation, and intelligent information processing. He has led approximately 40 important scientific research projects and published more than ten monographs and 100 papers in international journals and conferences. He is the author of three books: Theory of Neural Network Systems (Xidian University Press, 1990), Theory and Application on Nonlinear Transformation Functions (Xidian University Press, 1992), and Applications and Implementations of Neural Networks (Xidian University Press, 1996). He is the author or coauthor of more than 150 scientific papers.

Prof. Jiao is a member of the IEEE Xi’an Section Executive Committee, and the Chairman of Awards and Recognition Committee and an executive committee member of the Chinese Association of Artificial Intelligence.

Xiaodong Wang received the B.S. degree from Harbin Institute of Technology, Harbin, China, in 1998, and the M.S. degree from Inner Mongolia University of Technology, Hohhot, China, in 2007. He is currently working toward the Ph.D. degree in computer application technology at the School of Computer Science and Technology, Xidian University and the Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education of China, Xi’an, China.

His current research interests include convex optimization and its applications in compressive sensing and wireless networks.
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