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RESEARCH ARTICLE

A survey on distributed compressed sensing: theory and applications

Hongpeng YIN (✉)[1,2], Jinxing LI[1], Yi CHAI[1,3], Simon X. YANG[4]

1 College of Automation, Chongqing University, Chongqing 400030, China
2 Key Laboratory of Dependable Service Computing in Cyber Physical Society of Ministry of Education, Chongqing 400030, China
3 State Key Laboratory of Power Transmission Equipment and System Security and New Technology, Chongqing 400030, China
4 School of Engineering, University of Guelph, Guelph N1G 2W1, Canada

Abstract The compressed sensing (CS) theory makes sample rate relate to signal structure and content. CS samples and compresses the signal with far below Nyquist sampling frequency simultaneously. However, CS only considers the intra-signal correlations, without taking the correlations of the multi-signals into account. Distributed compressed sensing (DCS) is an extension of CS that takes advantage of both the inter- and intra-signal correlations, which is wildly used as a powerful method for the multi-signals sensing and compression in many fields. In this paper, the characteristics and related works of DCS are reviewed. The framework of DCS is introduced. As DCS's main portions, sparse representation, measurement matrix selection, and joint reconstruction are classified and summarized. The applications of DCS are also categorized and discussed. Finally, the conclusion remarks and the further research works are provided.

Keywords compressed sensing, distributed compressed sensing, sparse representation, measurement matrix, joint reconstruction, joint sparsity model

1 Introduction

In the past years, compressed sensing (CS) [1–3] has received much attention. CS explores a new method to solve the problem of high sampling frequency for signals. In comparison to the general compression scheme, the theory of CS can sample and compress the original signal with far below Nyquist sampling frequency simultaneously. It greatly improves the efficiency of the signal sampling and compression. CS is applicable to many situations, such as medical imaging [4–7], compressed imaging [8–10], and so on. The framework of CS combines the notions of sparse representation, measurement, and reconstruction which is shown in Fig.1 [11]. The source signals are represented sparsely using a certain sparse basis. Then the signals can be projected from high dimension to low dimension linearly using a measurement matrix which is incoherent with the sparse basis. A small number of measurements are acquired. Using a certain reconstruction algorithm, the source signals can be reconstructed accurately from the measurements.

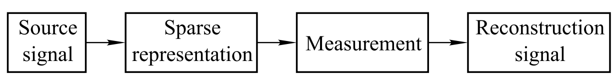

Fig. 1 The theoretical framework of CS

However, CS only considers the single signal processing and ignores the multi-correlations among signals. There is still large potential of development for CS. In order to exploit both inter- and intra-signal correlations, an extension

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E-mail: yinhongpeng@gmail.com

of CS named distributed compressed sensing (DCS) is presented by Baron et al. [12]. The theory of DCS is the integration of the distributed source coding (DSC) [13] and CS. DCS compresses each signal independently but reconstructs multi-signals jointly. The basic theoretical framework which mainly includes sparse representation, measurement, and joint reconstruction is shown in Fig. 2. It shows that if multiple source signals $\{x_j\}$, $j \in \{1, 2, \ldots, n\}$ are sparse in a certain basis, each signal can be observed or encoded using an another incoherent basis and obtain the measurements which are far less than the signal length. The small number of measurements are transmitted to the decoder. Under appropriate conditions, received data can be joint recovered to $\{\hat{x}_j\}$, $j \in \{1, 2, \ldots, n\}$ accurately at central decoder.

DCS has two remarkable properties. First, during encoding each signal is compressed, respectively. By taking advantage of the inter- and intra-signal correlations, DCS can decrease a large number of measurements. The result of experiment in [12] reveals that in practice the savings in the number of required measurements can be massive over separate CS decoding, especially when the common part dominates. Second, DCS does not reduce the complexity of the whole process but transfers the complexity from encoder to joint decoder. It is quite suitable for many distributed applications which require low computational complexity at the encoder, such as wireless sensor networks [14–21] and video coding [22–25].

Since the theory of DCS is put forward, many scholars pay attention to this domain. Distributed compressed sensing as the key words are put in the Web of Science and the Fig. 3(a) and 3(b) are obtained. Figure 3(a) shows the published frequency in the area of DCS between 2006 and February 2013. Cited frequency of publications in the area of DCS between 2006 and February 2013 is also shown in Fig. 3(b). Both figures demonstrate that DCS is a hot research field. DCS is proposed by Baron firstly [12]. Subsequently, Baron, Duarte and Wakin make a series of detailed introductions on it [26–28]. Phan et al. [29] propose a new algorithm with nonlinear iterative thresholding strategy for DCS. In their work, it is able to reconstruct all sources simultaneously by processing row by row of the compressed signals even when the number of compressed samples is lower than four times of the number of nonzero coefficients in the signals. However, the thresholding strategy in the algorithm is not flexible for real-world data. Zhang et al. [30] modify the orthogonal matching pursuit (OMP) by considering the reconstructed signal as side information and the common component of the signals is avoided calculating repeatedly. Nevertheless, the limitation of that algorithm is that the sources must be quite highly related. Moreover, a reconstruction algorithm based on an sparse Bayesian learning method is indicated in [31]. The correlation factors between each two related signals are introduced and the method can be applied to both random and optimized projection matrices. However, the step of computing each two signals' correlation factors will increase the

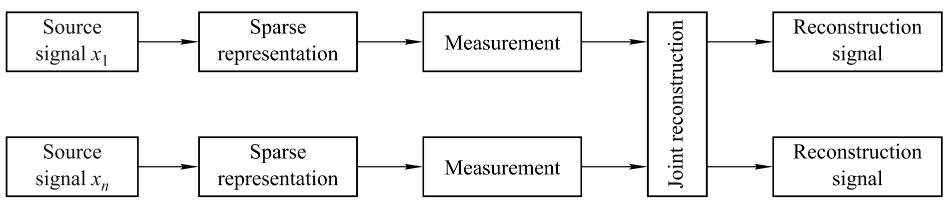

Fig. 2 The theoretical framework of DCS

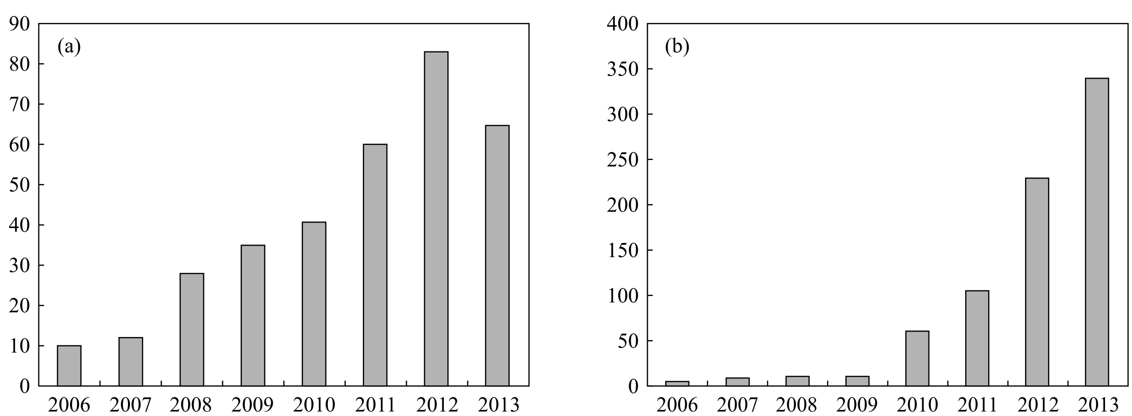

Fig. 3 (a) Frequency of publications in the area of distributed compressed sensing between 2006 and 2013; (b) cited frequency of publications in the area of distributed compressed sensing between 2006 and 2013

computational complexity, especially when the number of signals is large. In practice, DCS is also applied to many fields, such as video coding [22–25], image fusion [32], multi-input multi-output (MIMO) channel estimation [33], object recognition [34], and so on. For instance, Nagesh et al. [34] apply the DCS to face recognition. In their work, common features and innovation features in all training samples are grossly represented and a new test image can be well approximated using the two features from the same subject.

With the extensive study on DCS, however, there is few comprehensive survey of DCS. It is necessary to put out a review for scholars consulting. Recently, the research mainly concentrates on joint reconstruction algorithms which is the crux of the matter in this paper. The outline of this paper is organized as follows. In Section 2 and Section 3, the sparse representation and the selection of measurement matrix are analyzed. Section 4 explains the joint sparsity models (JSMs). Simultaneously, the reconstruction methods designed for DCS are classified. The main applications for DCS are also classified in Section 5. Finally, conclusion and further research about DCS are provided in Section 6.

2 Sparse representation

Sparse representation is the prime step for signal processing based on CS. Each signal is encoded independently in DCS. The methods of sparse representation for DCS are similar to CS. The basic idea of sparse representation is a kind of linear decomposition of multidimensional data if the original signals are sparse [35, 36]. The research in sparse representation can be broadly categorized as orthogonal basis, multi-scale geometric analysis, and over-complete dictionary.

Orthogonal basis The method of orthogonal basis is based on the theory of Harmonic analysis [37]. Commonly used bases include Fourier transform (FT) [38], short-time Fourier transform (STFT) [39], and Wavelet transform (WT) [40]. Among that three bases, the WT has the best ability of signal analysis and processing, and STFT is better than FT. FT processes the signal only in frequency domain. STFT processes the signal both in frequency and time domain. However, all the shapes and sizes of the time-frequency window in STFT are fixed. Different from the FT and STFT, WT provides variable time-frequency window which increases the ability of time-frequency localization. Nevertheless, the performance of sparsely representing the signal based on orthogonal basis is depended on whether the characteristics of the signals exactly match with the basis functions.

Multi-scale geometric analysis The method of multi-scale geometric analysis is generated from the theory of "optimal" image representation [41]. Multi-scale geometric analysis is proposed mainly to handle the sparse representation of multi-dimension signals, because of its properties of directivity, multi-resolution, and localization. In recent years, the typical methods of multi-scale geometric analysis are categorized as adaptive analysis and non-adaptive analysis. Adaptive multi-scale geometric analysis can adaptively change the basis function based on the content of the image. Adaptive multi-scale geometric analysis mainly includes Brushlet [42], Wedgelet [41], Beamlet [43], and Bandelet [44] et al. Different from adaptive multi-scale geometric analysis, the basis function of image transform of non-adaptive multi-scale geometric analysis is fixed. It mainly includes Ridgelet [45, 46], Curvelet [47], and Contourlet transform [48] et al. The cost time using non-adaptive multi-scale geometric analysis is smaller than adaptive multi-scale geometric analysis. However, the performance of sparse representation using non-adaptive multi-scale geometric analysis is worse than adaptive multi-scale geometric analysis.

Over-complete dictionary Over-complete dictionary is composed of a library of redundant elements instead of the only components of a single basis. The atoms can be acquired by constructing or training. There are two approaches to choose an over-complete dictionary. The first one is exploiting a prespecified transform matrix, such as over-complete Wavelets [49], Contourlets [50, 51], Curvelets [2], and short-time Fourier transforms [52]. The second one is designing dictionary which based on training, such as the method of optimal directions (MOD) [53], K-SVD [54], and generalized principal component analysis (GPCA) [55, 56]. The advantage of over-complete dictionary is that the redundancy atoms are changed based on source signals. Over-complete dictionary is considered as the most potential method to exceed the commonly dictionary. However, reducing the high computational complexity and selecting the training samples are still open problems.

In this section, the methods of different sparse representation are introduced. The methods of orthogonal bases especially WT are suitable for the processing of one-dimension signals. The multi-scale geometric analysis is an emerging research whose mathematical theories are still in development. However, there is no doubt that multi-scale geometric analysis is good for processing the image signals. Over-complete dictionary exploits the structural feature of signals and represents the signals adaptively. It is widely used in both one-dimension signals and image signals. Though there is some work left, over-complete dictionary has great potential in the future.

3 Measurement

The measurement is considered as a linear projection using a measurement matrix to obtain a number of measurements. The selection of measurement matrix is the key to the process of obtaining measurement vector and reconstruction. Assume that the reconstruction algorithm is unchangeable, the error between reconstructional signal and source is smaller with the increasing quality of measurement matrix. Thus, it is significant to research the measurement matrix.

From the view of principle, measurement matrix needs to satisfy two basic principles: restricted isometry property (RIP) and incoherence [57, 58]. Donoho [1] integrates that if the original signal can be sparsely represented in a certain basis, it is able to measure the signal by constructing a measurement matrix which is incoherent with the transformation matrix.

From the existing literatures, the researches on measurement matrix mainly concentrate on two aspects: random matrix and deterministic matrix.

Random matrix The random matrix is proposed by Candès and Romberg [59, 60] firstly. Recently, the most used random matrix contains random Gaussian measurement matrix [1, 2, 59, 60], random Bernoulli matrix [1, 2, 59], random Fourier measurement matrix [3,50,60], and relevant measurement matrix [2]. However, because of the uncertainty of random matrix, it is hard to be implemented in hardware.

Deterministic matrix In order to overcome the limitation of random matrix, some scholars propose the deterministic matrix: Hadamard matrix [2], partial Hadamard matrix [61], Toeplitz matrix [62–65], part of orthogonal matrix [66], and Circulant matrix [67, 68] et al. The deterministic matrix is better used in hardware than random matrix. However, the deterministic matrix does not have universality, but only for a specific category.

Although various measurement matrices are proposed, how to select the measurement matrix is still an open problem. Each kind of matrix has both advantages and disadvantages. For instance, partial Hadamard matrix [61] is designed by selecting M rows from $N \times N$ Hadamard matrix ($M < N$). In comparison to other matrices, partial Hadamard matrix needs less number of measurements for reconstruction. However, $N \times N$ Hadamard matrix must agree with $N = 2^k$ ($k = 1, 2, \ldots$) which limits the application of it. Thus most selection of measurement matrix is based on specific application so far. With consulting many references [63, 69–73] and taking experiments to estimation the performance of different kinds of measurement matrices (Toeplitz matrix, Gaussian matrix, Hadamard matrix, Fourier matrix, Bernoulli matrix and part of orthogonal matrix) in block signal processing, the conclusion is presented that the performance of Toeplitz matrix is optimal; other four measurement matrices have the similar properties which are better than the performance of Fourier matrix. Besides, the six kinds of matrices are compared to estimation the performance in spectrum estimation [69]. The conclusion is similar to ours. This could be a reference in selecting measurement matrix.

At present, the structure of measure matrix is not good enough. Although there are some having been implemented in hardware, such as Mishali's and Eldar's work [34, 74–77] on the modulated wideband converter, there is a lot of work left to do. One is how to design a novel type of measurement matrix which is more efficient and universal. In our opinions, we consider that the design of measurement matrix should satisfy two additional conditions as follows:

- Be easy and universal to be implemented by hardware or optimal algorithms.
- Be suitable for most of signals which could be sparse represented or compressed.

4 Reconstruction

In this section, the joint reconstruction algorithms for DCS are discussed. Different from CS, the algorithms for DCS are based on different joint sparsity models (JSMs). Different models correspond to different joint reconstruction algorithms.

4.1 Joint sparsity models

Joint sparsity models (JSMs) are the kernel of DCS. According to different application scenarios, various JSMs are put out. Based on [12, 26–28], three typical models are summarized. Besides, other possible types of models are presented.

JSM-1 To the first joint sparsity model (JSM-1), all of the signals consist of common components and innovation components. Each of the signals can be represented sparsely using a same sparse basis. In comparison to CS, this model utilizes the inter-signal correlations additionally between the different signals and avoids sampling the public part of each signal repeatedly. In a JSM-1 situation, each sensor separately represents and measures its signals and transfers a small number of the resulting measurements to a single collection point. By using the received measurements, the signals can be reconstructed precisely. That is,

$$x_j = z_C + z_j = \Psi\theta_C + \Psi\theta_j, \quad j \in \{1, 2, \ldots, J\}, \tag{1}$$

where $\{x_j\}$ is a related signal resemble and each $x_j \in R^N$. z_C and $\{z_j\}$ are the common component and innovation components, respectively. $\Psi = \{\psi_i\}_{i=1}^N$ is the sparse matrix. And the sparsity $K_C = ||\theta_C||_0$, $K_j = ||\theta_j||_0$.

JSM-1 has a wide application. A practical situation modeled by JSM-1 is video coding [22–25]. To a video, the frame blocks are approximately related to successive frames and they are around sparse signals in a certain basis. According to above, video coding conforms to JSM-1. By exploiting the correlations of frames, the common portions and innovation portions between frames can be extracted and compressed more efficiently. Obviously, the number of required measurements is decreased.

JSM-2 Unlike the JSM-1, the innovation portions under the second joint sparsity model (JSM-2) are equal to zero but all signals are constructed from only common components. In this model each signal is sparse on a certain basis, and the sparsity of each signal is same, but the sparse coefficients are different. That is,

$$x_j = \Psi\theta_j, \quad j \in \{1, 2, \ldots, J\}, \tag{2}$$

where θ_j contains the nonzero contents of x_j in Ψ, and $||\theta_j|| = K$. In other words, the signals well-processed by JSM-2 can be sparsely represented in a same sparse basis. The non-zero positions of each sparse coefficient vector is identical. Utilizing this common structural information, the signals can be recovered jointly.

The typical application by JSM-2 is fusion of infrared and visible image [78]. Visible and infrared images of the same scenario are highly related and both of them are also fit to be sparsely represented with a same sparse basis.

JSM-3 The third joint sparsity model (JSM-3) is an extension of JSM-1. The signal in JSM-3 also consists of common component and innovation component. The difference from JSM-1 is that the common component does not need to be sparse in any basis, however, the innovation component still needs to be sparse. That is,

$$x_j = z_C + z_j = z_C + \Psi\theta_j, \quad j \in \{1, 2, \ldots, J\}. \tag{3}$$

To JSM-3, it is unable to compress each signal separately by CS because the common portion is not sparse. Whereas, the shared common portion can still greatly reduce the rate of required measurements for reconstruction. In comparison to JSM-1 and JSM-2, the reconstructional signal is more accurate.

This model is suitable for the scenario that inter-signal correlation is strong but intra-signal correlation is weak. Therefore, JSM-3 is also applicable for video coding where the innovations between video frames may be sparse, though a single frame is not very sparse.

Others It should be noted that there are many possible joint sparsity models except the representative three (JSM-1, JSM-2, and JSM-3). Dror Baron et al. [12] consider that one immediate extension is a combination of JSM-1 and JSM-2, where the signals include innovation components (like in JSM-1) and a common set of sparse basis vector but with different coefficients (like in JSM-2). Moreover, if each innovational part of the signals has the same set of subscript, the JSM-3 could be extended to JSM-2. Combining the JSM-1 with JSM-3 is also a valuable method. The combination could be suitable for the situations whose common components are sparse or not. Recently, there are also some extensions of JSMs being indicated [15,79–84]. For instance, in [79] Luo et al. consider the inter-pixel relationship among the R (red), G (green) and B (blue) planes (color image) and extend the joint sparsity model. Not only they consider a global common, but also they consider three pair-wise common components (RG, RB, and GB). The extended model in [79] has a "sparser" joint representation.

Though there are some novel models having been proposed, most of them are the extensions of JSM-1, JSM-2 or JSM-3. Moreover, majority of the proposed models are used for wireless sensor networks (WSNs). It is also a challenge to research novel joint sparse models that can be applied to wider application scenarios.

4.2 Joint reconstruction algorithms

Signal reconstruction refers to recovery the data from low dimension to high dimension. Currently, many algorithms for CS have been proposed, such as gradient projection method [67, 85], matching pursuit algorithm [86], orthogonal matching pursuit algorithm [87, 88] and chaining pursuit (CP) [89]. However, different from CS, the recovery method for DCS is joint. In recent years, some joint recovery algorithms which are adapt to DCS are presented. However, previous references have not effectively classified the joint reconstruction algorithms. In this section, we focus on joint recovery approaches of the typical models (JSM-1, JSM-2, and JSM-3).

Reconstruction for JSM-1 To the signal ensemble which adapts to JSM-1, Baron et al. [26] take use of the weighted l_1 norm minimization to perform recovery. Such joint reconstruction method is shown to outperform separate reconstruction methods, especially when the the common component of signal ensemble is relatively large. Nevertheless, the optimal weights depend on the relative sparsity of each components may be unacceptable. And the achievable measurement rate region of this method is too loose. Therefore, Baron et al. exploit a single linear program to reconstruct the signals jointly. However, the complexity of such algorithm is quite cubic. Thus, novel recovery methods with simpler operations are desirable.

Some scholars have made efforts to find alternative recovery algorithms for JSM-1. A new algorithm is developed by Schnelle et al. [90]. The proposed method separates the recovery of the innovation and common components into two stages, that in some cases significantly reduces the number of measurements. Nevertheless, the authors of that paper assume that the sum of the innovation parts in signals tends to zero when the number of signals is relatively large. Obviously, the assumption is irrational when all innovations are very sparse. With the use of annihilating filter approach, another reconstruction algorithm is pointed out by Hormati [91], where the required number of measurements approximate the limit for perfect reconstruction. But this algorithm requires the knowledge of sparsity at the encoder. In addition, Liang and Liu [92] present a robust method for joint spectrum reconstruction, but without available and analytical results. Inspired by the interference cancellation method [93], Xu [94] introduces a novel joint decoding method which separates the recovery into two iterative stages and each stage is made up of extraction sparse recovery. In comparison to separate recovery, when the signal dimensions are large, this algorithm reduces RIP order with a small penalty on the restricted isometry constants. In addition, other state-of-the-art reconstruction methods are proposed in [30, 91, 95–97].

Though some reconstruction algorithms for JSM-1 have been proposed, some problems still exist:

- Requirement for high correlations of the signals. A large amount of algorithms for JSM-1 need high correlations about multi-signals. However, it is strict to some scenarios, such as the object in video moves very fast.
- Number of measurements. It is necessary to reduce the number of measurements while ensuring the construction quality.
- Robustness. The robustness of the algorithm is also necessary, especially the source is polluted with noise after sampling.

Reconstruction for JSM-2 To JSM-2, reconstructing each signal separately via l_0 norm minimization needs K+1 (K is the sparsity) measurements per signal, while taking use of l_1 norm minimization would demand cK (c is oversampling [98]) measurements per signal. Obviously, it is important to propose joint recovery methods for JSM-2 to reduce the number of measurements.

Duarte et al. [27] indicate one-step greedy algorithm (OSGA) to recovery the source signals. The OSGA algorithm is based on iterative principle of greedy algorithm. Using the prior knowledge of sparse coefficient, decoding the signals jointly is realizable. Especially when the number of original data is very large, the signal can be reconstructed accurately with a small number of measurements. Nevertheless, reconstruction effect is not very ideal when data is few. Another approach-simultaneous orthogonal matching pursuit (SOMP) [27] is proposed by Duarte et al, which is adapt to the condition when the number of source signals is few. Because of the orthogonalized dictionary, calculation speed is improved greatly in this algorithm. Moreover, Wang and Zhu [83] employ iterative-OMP to DCS and the reconstruction speed and accuracy are improved. However, this method still cannot overcome the limitations of OMP methods. Based on backtracking technique and sparsity adaptive matching pursuit (SAMP) [99], a new joint recovery method refers to DCS-SAMP is proposed by Wang [100]. Succeed to the advantages of SAMP, the complexity of this algorithm is lower than OMP and this method can also operate both in the noisy and noiseless regime. But the signal ensemble suited for this method must be very sparse.

Up till now, a few reconstruction approaches have been proposed and the most of study for JSM-2 is MIMO communication. Thus, the research for JSM-2 remains an open issue.

Reconstruction for JSM-3 To JSM-3, z_C cannot be reconstructed via CS techniques when it is not sparse. However, the common component makes it possible to reduce the number of measurements substantially. A recovery algorithm which is dubbed transpose estimation of common component (TECC) is provided by Wakin and Sarvotham [28]. TECC exploits simple linear algebra to reconstruct the signal. Although this algorithm is simple, the accuracy of reconstruction is not satisfied. Another reconstruction algorithm has been introduced in [28]. This method removes the measurements to aid in estimating the common component and saves the number of measurements. However, the complexity of computation is higher than TECC.

JSM-3 extends JSM-1. This model also exists in sensor networks, with a background signal that is not sparse. However, the common components of most scenarios are sparse, so it does not need to detach the parts which are not sparse. In comparison to JSM-3, JSM-1 has a more popular use. Thus, a few scholars research JSM-3. However, we consider that JSM-3 has the potential to be developed. If the algorithm for JSM-3 is improved to be able to reconstruct the signals whose common components are sparse or not, the JSM-3 will have a wider application. To JSM-2, it is suitable for some situations where the same signals are acquired by multiple sensors but with phase shifts, such as in many acoustic localizations and array processing algorithms.

5 Applications

The DCS has been widely applied to many domains that shift a significant portion of the computational load from the encoder to the decoder or allow a joint decoding without any need of information exchange among the coders.

Video coding In order to meet the novel scenarios of video [101] (wireless monitoring network, wireless PC camera, and camera phone et al.), it is necessary to reduce the computational complexity at encoder. Prades-Nebot [22] proposes a new distributed video coding framework based on DCS, dubbed distributed compressed video sensing (DCVS). In his work, video frames are categorized as K-frames and CS-frames. The K-frames are encoded using a conventional intra-frame coder while the CS-frames are encoded using CS principles. Nevertheless, the limitation of this framework is not making full use of the correlations between video frames. In the same year, Do [23] proposes another framework of DCVS (called DISCOS) which divides the CS-frames into block-based measurements and frame-based measurements. In comparison to the method in [22], DISCOS makes more full use of the correlations between video frames. However, this framework leaves out the feedback which may result that the number of measurements is inadequate or excessive. What is more, both the frameworks described in [22] and [23] only encode the CS-frames using CS but the key frames are still encoded by the universal frame coding method. Kang [24] puts out a novel framework which encodes the key frames by CS. This framework has become the highest recognition framework of DCVS currently. Besides, a multiple description DCVS (MD-DCVS) for the robust transmission of low-power video devices is indicated by Yu et al. [25].

Wireless sensor networks Wireless sensor networks (WSNs) [102] are a rising technology which promise to monitor the physical phenomenon by a spatially distributed network of inexpensive and small wireless devices. The properties of DCS, such as computational asymmetry, tolerance to quantization and noise, robustness to measurement loss, and scalability, make it well-suited for sensor network applications. In [15], the author applies the DCS to WSNs and proposes a new recovery algorithm which can reduce the energy consumption without compromising the estimated reliability of the application. Nevertheless, the sparsity of the signal in [15] has to be known before the signal is transferred. It is difficult to realize in actual WSNs. A novel DCS method based on local regional data is presented by Yang et al. [16]. On the foundational theory of DCS, the method analyzes the structure of signals which are gathered by the sensors in local regions. What is more, spatial−temporal correlation is considered to design the measure matrix. Applying this approach to WSNs, the signals could be reconstructed stably and accurately even if their sparsity could not be known beforehand. In addition, other examples that apply DCS to WSNs are discuss in [17–21].

Image fusion Image fusion [103] combines at least two images of the same situation into a single image which is suitable for practical applications and human perception. In [52], Yin and Li design a multimodal image fusion method based on the JSM-1. The measurements of the common and innovation components of the images are fused. And the effectiveness of this new fusion method is more satisfied than traditional methods. An appropriate fusion of infrared and visible images can combine the complementary information and obtain a more exact, reliable and better description of the environmental conditions. A fusion of infrared and visible images based on JSM-2 is presented by Chen and Yang [78]. In that method, the sparse coefficients of infrared and visible images are combined according to activity and details level of each sliding window. The experimental results indicate that the proposed method performs better than the conventional approaches. In addition, the similar fusion methods has also been proposed in [32, 104].

Others Except the applications introduced above, DCS has also been found in many other application domains. Wang et al. [21] use the theory to multichannel electrocardiography (ECG) signals joint acquisition and reconstruction. DCS is also applied to joint channel estimation [105, 106], MIMO channel [33, 83, 107, 108], data fusion [84, 104], ground moving target indication (GMIT) [109], and speech enhancement (SE) [110] et al.

6 Conclusions and further research

DCS is most suitable for the applications that require low complexity and/or low power consumption at the encoder. This survey provides a snapshot of remarkable research in the area of DCS, but is by no means perfect. It can be foreseen that this relatively new topic will remain a potential field of research in the coming years, which will bring further significant progresses and developments.

It should be noted that some more work still needs to be done in this domain of research though significant success has been achieved. The further work could be included as follows.

Decrease computational requirement and running time

Even though many algorithms have been proposed, we observe in this paper that most of them are yet to be deployable. Most of the algorithms are mainly based on single measurement vector (SMV), which means convert multi-dimensional signal to one-dimensional signal. These algorithms, however, are known to have some conventional problems such as high complexity, strong reliance on the initial parameters, and slow convergence. Thus, new approaches are needed to overcome these limitations.

Novel joint sparsity model

By taking advantage of the three typical joint sparsity models, a majority of various signals can be processed. However, some scenes are still not covered by these three typical joint sparsity models, such as the video with many fast moving objects and activities, and the signals in multi-view but with phase shift. It is still an open challenge.

Test in complex condition

Many algorithms for DCS deal with highly structured scenes. There is necessity to test performance of these methods in unstructured situations. More research attention should be pay to the development of frameworks that will also effectively deal with the problem of scalability of WSNs, video coding, and channel estimation et al. in the real world of cluttered environments.

Application prospect

DCS is efficiently used in variety of distributed applications because of its capabilities of local data compression and joint reconstruction. Combining DCS with other areas such as signal detection, feature extraction and fault diagnosis et al, will be a further significant domain in the near future. Especially, the theory of DCS is quite suitable for WSNs. In recent years, many frameworks of WSNs are proposed using DCS. DCS takes advantage of a sparsity property of the sensors' signals and allows their joint reconstruction from a small number of measurements. However, most of the presented frameworks of WSNs don't make full use of the correlations. With the development of DCS and WSNs, we consider that the cross-over study of them is focused on taking advantage of both temporal and spatial correlations of sensed signals.

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References

1. Donoho D L. Compressed sensing. IEEE Transactions on Information Theory, 2006, 52(4): 1289–1306
2. Tsaig Y, Donoho D L. Extensions of compressed sensing. Signal processing, 2006, 86(3): 549–571
3. Candès E J. Compressive sampling. In: Proceedings of the international congress of mathematicians. 2006, 1433–1452
4. Lustig M, Donoho D, Pauly J. Rapid mr imaging with compressed sensing and randomly under-sampled 3DFT trajectories. In: Proceedings of the 14th Annual Meeting ISMRM. 2006
5. Lustig M, Lee J H, Donoho D L, Pauly J M. Faster imaging with randomly perturbed, under-sampled spirals and l1 reconstruction. In: Proceedings of the 13th Annual Meeting of ISMRM. 2005, 685
6. Lustig M, Santos J M, Lee J H, Donoho D L, Pauly J M. Application of compressed sensing for rapid MR imaging. In: Proceedings of Work. Struc. Parc. Rep. Adap. Signaux (SPARS). 2005
7. Trzasko J, Manduca A. Highly undersampled magnetic resonance image reconstruction via homotopic-minimization. IEEE Transactions on Medical imaging, 2009, 28(1): 106–121
8. Baraniuk R G. Single-pixel imaging via compressive sampling. IEEE Signal Processing Magazine, 2008
9. Marcia R F, Harmany Z T, Willett R M. Compressive coded aperture imaging. In: IS&T/SPIE Electronic Imaging. 2009, 72460G–72460G
10. Robucci R, Chiu L K, Gray J, Romberg J, Hasler P, Anderson D. Compressive sensing on a cmos separable transform image sensor. In: Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing. 2008, 5125–5128
11. Yin H, Liu Z, Chai Y, Jiao X. A survey of compressed sensing. Control and Decision, 2013, 28(10): 1441–1445
12. Baron D, Wakin M B, Duarte M F, Sarvotham S, Baraniuk R G. Distributed compressed sensing, 2005
13. Slepian D, Wolf J K. Noiseless coding of correlated information sources. IEEE Transactions on Information Theory, 1973, 19(4): 471–480
14. Tropp J A, Gilbert A C, Strauss M J. Simultaneous sparse approxi-

mation via greedy pursuit. In: Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing. 2005, 721–724

15. Hu H, Yang Z. Spatial correlation-based distributed compressed sensing in wireless sensor networks. In: Proceedings of the 2010 6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM). 2010, 1–4
16. Yang H, Huang L, Xu H, Liu A. Distributed compressed sensing in wireless local area networks. International Journal of Communication Systems, 2013
17. Golbabaee M, Vandergheynst P. Distributed compressed sensing for sensor networks using thresholding. In: Proceedings of the SPIE Optical Engineering and Applications. 2009
18. Liu Y, Zhu X, Zhang L, Cho S H. Distributed compressed video sensing in camera sensor networks. International Journal of Distributed Sensor Networks, 2012, Artide 352167
19. Puri R, Ramchandran K. Prism: A new robust video coding architecture based on distributed compression principles. In: Proceedings of the Annual Allerton Conference on Communication Control and Computing. 2002, 586–595
20. Hu H F, Yang Z. An energy-efficient distributed compressed sensing architecture for wireless sensor networks based on a distributed wavelet compression algorithm. In: Proceedings of the 2011 International Conference on Wireless Communications and Signal Processing. 2011
21. Wang Q, Liu Z. A novel distributed compressed sensing algorithm for multichannel electrocardiography signals. In: Proceedings of 2011 4th International Conference on Biomedical Engineering and Informatics. 2011, 607–611
22. Prades-Nebot J, Ma Y, Huang T. Distributed video coding using compressive sampling. In: Proceedings of the 2009 Picture Coding Symposium. 2009, 1–4
23. Do T T, Chen Y, Nguyen D T, Nguyen N, Gan L, Tran T D. Distributed compressed video sensing. In: Proceedings of the 16th IEEE International Conference on Image Processing (ICIP). 2009, 1393–1396
24. Kang L W, Lu C S. Distributed compressive video sensing. In: Proceedings of the 2009 IEEE International Conference on Acoustics, Speech and Signal Processing. 2009, 1169–1172
25. Yu D, Wang A, Zhao M. A multiple description distributed compressed video sensing for robust transmission. In: Proceedings of 2012 International Conference on Computing, Measurement, Control and Sensor Network. 2012, 13–16
26. Baron D, Duarte M F, Sarvotham S, Wakin M B, Baraniuk R G. An information-theoretic approach to distributed compressed sensing. In: Proceedings of the 45rd Conference on Communication, Control, and Computing. 2005
27. Duarte M F, Sarvotham S, Baron D, Wakin M B, Baraniuk R G. Distributed compressed sensing of jointly sparse signals. In: Proceedings of Asilomar Conf. Signals, Sys., Comput. 2005, 1537–1541
28. Wakin M B, Duarte M F, Sarvotham S, Baron D, Baraniuk R G. Recovery of jointly sparse signals from few random projections. In: Proceedings of Neural Information Processing Systems Foundation. 2005
29. Phan A H, Cichocki A, Nguyen K S. Simple and efficient algorithm for distributed compressed sensing. In: Proceedings of the 2008 IEEE Workshop on Machine Learning for Signal Processing. 2008, 61–66
30. Zhang W, Ma C, Wang W, Liu Y, Zhang L. Side information based orthogonal matching pursuit in distributed compressed sensing. In: Proceedings of the 2nd IEEE International Conference on Network Infrastructure and Digital Content. 2010, 80–84
31. Vinuelas-Peris P, Artes-Rodriguez A. Bayesian joint recovery of correlated signals in distributed compressed sensing. In: Proceedings of the 2nd International Workshop on Cognitive Information Processing (CIP). 2010, 382–387
32. Yu N, Qiu T, Bi F, Wang A. Image features extraction and fusion based on joint sparse representation. IEEE Journal of Selected Topics in Signal Processing, 2011, 5(5): 1074–1082
33. Tan Y, Xu W, He Z, Tian B, Wang D. Mimo-ofdm channel estimation based on distributed compressed sensing and kalman filter. In: Proceedings of the 2011 IEEE International Conference on Signal Processing, Communications and Computing. 2011
34. Nagesh P, Li B. A compressive sensing approach for expression-invariant face recognition. In: Proceedings of the 2009 IEEE Conference on Computer Vision and Pattern Recognition. 2009, 1518–1525
35. Cheng H, Liu Z, Yang L, Chen X. Sparse representation and learning in visual recognition: theory and applications. Signal Processing, 2013, 93(6): 1408–1425
36. Ma X, Quang Luong H, Philips W, Song H, Cui H. Sparse representation and position prior based face hallucination upon classified overcomplete dictionaries. Signal Processing, 2012, 92(9): 2066–2074
37. Donoho D L, Flesia A G. Can recent innovations in harmonic analysisexplain'key findings in natural image statistics? Network: Computation in Neural Systems, 2001, 12(3): 371–393
38. Chew W, Song J. Fast fourier transform of sparse spatial data to sparse fourier data. In: Proceedings of IEEE Antennas and Propagation Society, AP-S International Symposium (Digest). 2000, 2324–2327
39. Nawab S H, Dorken E. Efficient stft approximation using a quantization and differencing method. In: Proceedings of the 1993 IEEE International Conference on Acoustics, Speech, and Signal Processing. 1993, 587–590
40. Selesnick I W. Sparse signal representations using the tunable q-factor wavelet transform. In: Proceedings of SPIE Optical Engineering and Applications. 2011
41. Donoho D L. Wedgelets: nearly minimax estimation of edges. The Annals of Statistics, 1999, 27(3): 859–897
42. Meyer F G, Coifman R R. Brushlets: a tool for directional image analysis and image compression. Applied and computational harmonic analysis, 1997, 4(2): 147–187
43. Huo X, Donoho D. Beamlets and multiscale image analysis. Multiscale and Multiresolution Methods, 2002, 149–196
44. Le Pennec E, Mallat S. Image compression with geometrical wavelets. In: Proceedings of the 2000 International Conference on Image Processing. 2000, 661–664
45. Candes E J, Donoho D L. Ridgelets: A key to higher-dimensional intermittency. Philosophical Transactions of the Royal Society, 1999, 357(1760): 2495–2509
46. Donoho D L. Orthonormal ridgelets and linear singularities. SIAM Journal on Mathematical Analysis, 2000, 31(5): 1062–1099
47. Candes E J, Donoho D L. Curvelets: A Surprisingly Effective Non-

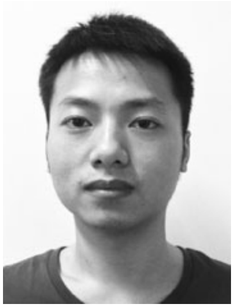
adaptive Representation for Objects With Edges. Technical report, DTIC Document. 2000

48. Do M N, Vetterli M. Contourlets. Studies in Computational Mathematics, 2003, 10: 83–105
49. Fong H, Zhang Q, Wei S. Image reconstruction based on sub-gaussian random projection. In: Proceedings of the 4th International Conference on Image and Graphics. 2007, 210–214
50. Candes E J, Tao T. Near-optimal signal recovery from random projections: Universal encoding strategies? IEEE Transactions on Information Theory, 2006, 52(12): 5406–5425
51. Bi X, Chen X D, Zhang Y, Liu B. Image compressed sensing based on wavelet transform in contourlet domain. Signal Processing, 2011, 91(5): 1085–1092
52. Yin H, Li S. Multimodal image fusion with joint sparsity model. Optical Engineering, 2011, 50(6): 067007–067007
53. Engan K, Aase S O, Husøy J H. Multi-frame compression: theory and design. Signal Processing, 2000, 80(10): 2121–2140
54. Aharon M, Elad M, Bruckstein A. K-svd: An algorithm for designing overcomplete dictionaries for sparse representation. IEEE Transactions on Signal Processing, 2006, 54(11): 4311–4322
55. Rubinstein R, Bruckstein A M, Elad M. Dictionaries for sparse representation modeling. Proceedings of the IEEE, 2010, 98(6): 1045–1057
56. Dong W, Li X, Zhang D, Shi G. Sparsity-based image denoising via dictionary learning and structural clustering. In: Proceedings of the 2011 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2011, 457–464
57. Baraniuk R, Davenport M, DeVore R, Wakin M. A simple proof of the restricted isometry property for random matrices. Constructive Approximation, 2008, 28(3): 253–263
58. Candes E J. The restricted isometry property and its implications for compressed sensing. Comptes Rendus Mathematique, 2008, 346(9): 589–592
59. Candès E J, Romberg J, Tao T. Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information. IEEE Transactions on Information Theory, 2006, 52(2): 489–509
60. Candes E J, Romberg J K, Tao T. Stable signal recovery from incomplete and inaccurate measurements. Communications on pure and applied mathematics, 2006, 59(8): 1207–1223
61. Haghighatshoar S, Abbe E, Telatar E. Adaptive sensing using deterministic partial hadamard matrices. In: Proceedings of the 2012 IEEE International Symposium on Information Theory Proceedings (ISIT). 2012, 1842–1846
62. Yin W, Morgan S, Yang J, Zhang Y. Practical compressive sensing with toeplitz and circulant matrices. In: Proceedings of the 2010 Visual Communications and Image Processing. 2010, Article 77440K
63. Bajwa W U, Haupt J D, Raz G M, Wright S J, Nowak R D. Toeplitz-structured compressed sensing matrices. In: Proceedings of IEEE/SP 14th Workshop on Statistical Signal Processing. 2007, 294–298
64. Sebert F, Zou Y M, Ying L. Toeplitz block matrices in compressed sensing and their applications in imaging. In: Proceedings of the 2008 International Conference on Information Technology and Applications in Biomedicine. 2008, 47–50
65. Rauhut H. Circulant and Toeplitz Matrices in Compressed Sensing. arXiv.ovg>cs>arXiv:0902.4394. 2009
66. Li Z, Wu X, Peng H. Nonnegative matrix factorization on orthogonal subspace. Pattern Recognition Letters, 2010, 31(9): 905–911
67. Applebaum L, Howard S D, Searle S, Calderbank R. Chirp sensing codes: deterministic compressed sensing measurements for fast recovery. Applied and Computational Harmonic Analysis, 2009, 26(2): 283–290
68. Romberg J. Sensing by random convolution. In: Proceedings of the 2nd IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing. 2007, 137–140
69. Wang K, Chen J Z, Zhu Y G, Niu Y T. Comparison and analysis of the performance on measurement matrix to spectrum estimation. In: Proceedings of the 2012 National Conference on Information Technology and Computer Science. 2012, 1034–1037
70. Haupt J, Bajwa W U, Raz G, Nowak R. Toeplitz compressed sensing matrices with applications to sparse channel estimation. IEEE Transactions on Information Theory, 2010, 56(11): 5862–5875
71. Wang K, Liu Y, Chen S. Measurement matrix in compressed sensing of ir-uwb signal. In: Proceedings of the 2012 International Conference on Systems and Informatics (ICSAI). 2012, 2084–2088
72. Sun R, Zhao H, Xu H. The application of improved hadamard measurement matrix in compressed sensing. In: Proceedings of the 2012 International Conference on Systems and Informatics. 2012, 1994–1997
73. Yu Y, Petropulu A P, Poor H V. Measurement matrix design for compressive sensing–based mimo radar. IEEE Transactions on Signal Processing, 2011, 59(11): 5338–5352
74. Mishali M, Elron A, Eldar Y C. Sub-nyquist processing with the modulated wideband converter. In: Proceedings of the 2010 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP). 2010, 3626–3629
75. Mishali M, Eldar Y C, Elron A J. Xampling: Signal acquisition and processing in union of subspaces. IEEE Transactions on Signal Processing, 2011, 59(10): 4719–4734
76. Mishali M, Eldar Y C. Expected rip: conditioning of the modulated wideband converter. In: Proceedings of the 2009 Information Theory Workshop. 2009, 343–347
77. Chen Y, Mishali M, Eldar Y C, Hero A O. Modulated wideband converter with non-ideal lowpass filters. In: Proceedings of the 2010 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP). 2010, 3630–3633
78. Chen Y, Xiao G. Fusion of infrared and visible images based on distributed compressive sensing. In: Proceedings of WAP Conference Series: Information Science and Technology
79. Luo J, Yang B, Chen Z. Color image restoration via extended joint sparse model. In: Proceedings of Communications in Computer and Information Science, Pattern Recognition. 2012, 321: 497–504
80. Roy O, Hormati A, Lu Y M, Vetterli M. Distributed sensing of signals linked by sparse filtering. In: Proceedings of the 2009 IEEE International Conference on Acoustics, Speech and Signal Processing. 2009, 2409–2412
81. Hormati A, Roy O, Lu Y M, Vetterli M. Distributed sampling of signals linked by sparse filtering: theory and applications. IEEE Transactions on Signal Processing, 2010, 58(3): 1095–1109
82. Wang X, Fang H, Zhu X, Li B, Liu Y. Sparse filter correlation model

based joint reconstruction in distributed compressive video sensing. In: Proceedings of the 2nd IEEE International Conference on Network Infrastructure and Digital Content. 2010, 483–487

83. Wang H Q, Zhu X H, Li Y S. Parameter estimation for transmit diversity mimo radar based on distributed compressed sensing. Systems Engineering and Electronics, 2012, 34(12): 2463–2467
84. Kang J, Tang L, Zuo X, Li A, Li H. Distributed compressed sensing-based data fusion in sensor networks. In: Proceedings of the 1st International Conference on Pervasive Computing Signal Processing and Applications (PCSPA). 2010, 1083–1086
85. Li Z L, Chen H J, Yao C, Li J P. Compressed sensing reconstruction algorithm based on spectral projected gradient pursuit. Acta Automatica Sinica, 2012, 38(7): 1218–1223 (in Chinese)
86. Mallat S G, Zhang Z. Matching pursuits with time-frequency dictionaries. IEEE Transactions on Signal Processing, 1993, 41(12): 3397–3415
87. Tropp J A, Gilbert A C. Signal recovery from random measurements via orthogonal matching pursuit. IEEE Transactions on Information Theory, 2007, 53(12): 4655–4666
88. Fang H, Yang H R. Greedy algorithms and compressed sensing. Acta Automatica Sinica, 2011, 37(12): 1413–1421 (in Chinese)
89. Gilbert A C, Strauss M J, Tropp J A, Vershynin R. Algorithmic linear dimension reduction in the l_1 norm for sparse vectors. In: Proceedings of the 44th Annual Allerton Conference Communication Contron and Computing. 2006
90. Schnelle S R, Laska J N, Hegde C, Duarte M F, Davenport M A, Baraniuk R G. Texas hold'em algorithms for distributed compressive sensing. In: Proceedings of the 2010 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP). 2010, 2886–2889
91. Hormati A, Vetterli M. Distributed compressed sensing: Sparsity models and reconstruction algorithms using annihilating filter. In: Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing. 2008, 5141–5144
92. Liang J, Liu Y, Zhang W, Xu Y, Gan X, Wang X. Joint compressive sensing in wideband cognitive networks. In: Proceedings of the 2010 Wireless Communications and Networking Conference (WCNC). 2010, 1–5
93. Davenport M A, Boufounos P T, Baraniuk R G. Compressive domain interference cancellation. Technical report, DTIC Document. 2009
94. Xu W, Lin J, Niu K, He Z. A joint recovery algorithm for distributed compressed sensing. Transactions on Emerging Telecommunications Technologies, 2012, 23(6): 550–559
95. Sundman D, Saikat C, Skoglund M. A greedy pursuit algorithm for distributed compressed sensing. In: Proceedings of the 2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2012, 2729–2732
96. Shen M, Zhang Q, Yang J. A novel receive beamforming approach of ultrasound signals based on distributed compressed sensing. In: Proceedings of Instrumentation and Measurement Technology Conference (I2MTC). 2011, 1–5
97. Wang X, Guo W, Lu Y, Wang W. Distributed compressed sensing for block-sparse signals. In: Proceedings of the 2011 IEEE 22nd International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC). 2011, 695–699
98. Donoho D L. High-dimensional centrally symmetric polytopes with neighborliness proportional to dimension. Discrete & Computational Geometry, 2006, 35(4): 617–652
99. Do T T, Gan L, Nguyen N, Tran T D. Sparsity adaptive matching pursuit algorithm for practical compressed sensing. In: Proceedings of the 42nd Asilomar Conference Signals, Systems and Computers. 2008, 581–587
100. Wang Q, Liu Z. A robust and efficient algorithm for distributed compressed sensing. Computers & Electrical Engineering, 2011, 37(6): 916–926
101. Ndjiki-Nya P, Doshkov D, Kaprykowsky H, Zhang F, Bull D, Wiegand T. Perception-oriented video coding based on image analysis and completion: a review. Signal Processing: Image Communication, 2012, 27(6): 579–594
102. Yick J, Mukherjee B, Ghosal D. Wireless sensor network survey. Computer networks, 2008, 52(12): 2292–2330
103. Rahman S M, Ahmad M O, Swamy M. Contrast-based fusion of noisy images using discrete wavelet transform. Image Processing, IET, 2010, 4(5): 374–384
104. Yang A Y, Maji S, Hong K, Yan P, Sastry S S. Distributed compression and fusion of nonnegative sparse signals for multiple-view object recognition. In: Proceedings of the 12th International Conference on Information Fusion. 2009, 1867–1874
105. Wang W G, Yang Z, Hu H F. The method of achieving simultaneous channels estimation on distributed compressed sensing. Signal Processing (Xinhao Chuli), 2012, 28(6): 778–784 (in Chinese)
106. Wang D H, Niu K, He Z Q, Tian B Y. Channel estimation based on distributed compressed sensing in amplify-and-forward relay networks. The Journal of China Universities of Posts and Telecommunications, 2010, 17(5): 44–49
107. Corroy S, Mathar R. Distributed compressed sensing for the mimo mac with correlated sources. In: Proceedings of the 2012 IEEE International Conference on Communications (ICC). 2012, 2516–2520
108. Li Y, Song R. A new compressive feedback scheme based on distributed compressed sensing for time-correlated mimo channel. KSII Transactions on Internet & Information Systems, 2012, 6(2)
109. Prunte L. Application of distributed compressed sensing for gmti purposes. In: Proceedings of IET International Conference on Radar Systems (Radar 2012). 2012, 1–6
110. Wu D, Zhu W P, Swamy M. Compressive sensing-based speech enhancement in non-sparse noisy environments. IET Signal Processing, 2013, 7(5): 450–457

Hongpeng Yin received the BE degree in College of Communication Engineering, Chongqing University in 2003. Then he received PhD degree in control theory and control engineering, Chongqing University. His research interests include computer vision and pattern recognition.



Jinxing Li received the BE degree from Hangzhou Dianzi University in 2012. He is currently working towards the MSc degree at the College of Automation, Chongqing University. His research interests include compressed sensing and computer vision.

Yi Chai received the BE degree from National University of Defense Technology in 1982. He received the MSc and PhD degrees from Chongqing University in 1994 and 2001, respectively. He is the associate dean of the College of Automation, Chongqing University. His research interests include information processing, integration and control, and computer network and system control.

Simon X. Yang received the BE degree in engineering physics from Peking University, Beijing, China, in 1987, the MSc degree in biophysics from the Chinese Academy of Sciences, Beijing, China, in 1990, the MSc degree in electrical engineering from the University of Houston, Houston, TX in 1996, and the PhD degree in electrical and computer engineering from the University of Alberta, Edmonton, AB, Canada in 1999.