Wavelet-based Bayesian Algorithm for Distributed Compressed Sensing

Razieh Torkamani*
Faculty of Electrical Engineering, K.N. Toosi University of Technology, Tehran, Iran
rtorkamani@mail.kntu.ac.ir
Ramazan Ali Sadeghzadeh
Faculty of Electrical Engineering, K.N. Toosi University of Technology, Tehran, Iran
sadeghz@eetd.kntu.ac.ir

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Abstract
The emerging field of compressive sensing enables the reconstruction of the signal from a small set of linear projections. Traditional compressive sensing approaches deal with a single signal; while one can jointly reconstruct multiple signals via distributed compressive sensing algorithm, which exploits both the inter- and intra-signal correlations via joint sparsity models. Since the wavelet coefficients of many signals is sparse, in this paper, the wavelet transform is used as sparsifying transform, and a new wavelet-based Bayesian distributed compressive sensing algorithm is proposed, which takes into account the inter-scale dependencies among the wavelet coefficients via hidden Markov tree model, as well as the inter-signal correlations. This paper uses Bayesian procedure to statistically model this correlation via the prior distributions. Also, in this work, a type-1 joint sparsity model is used for jointly sparse signals, in which every sparse coefficient vector is considered as the sum of a common component and an innovation component. In order to jointly reconstruct multiple sparse signals, the centralized approach is used in distributed compressive sensing, in which all the data is processed in the fusion center. Also, variational Bayes procedure is used to infer the posterior distributions of unknown variables. Simulation results demonstrate that the structure exploited within the wavelet coefficients provides superior performance in terms of average reconstruction error and structural similarity index.

Keywords: Distributed Compressive Sensing; Joint Saprsity; Signal Reconstruction; Wavelet Transform; Hidden Markov Tree Model; Variational Bayes.

1- Introduction

Compressive sensing (CS) constitutes a framework for sampling of the signals at a rate lower than the Shannon-Nyquist sampling rate [1, 2, 3]. According to the CS theory, when the signal has a sparse representation in a particular basis, one can reconstruct the original signal from a reduced number of linear projections. In order to recover the original signal from compressed measurements, CS exploits the sparsity, i.e. the intra-signal correlation of the signal. But in some applications, the signals may possess many dependencies, which is referred to as inter-signal correlation. Distributed CS (DCS), as a generalization of CS, is proposed in [4- 6], and aims to exploit the intra- and inter-signal correlations simultaneously, and jointly reconstruct a set of signals. According to the DCS algorithm, in addition to each signal being individually sparse, some of their nonzero components are common. Since the signals share a common support in DCS, they can be jointly reconstructed from dramatically fewer measurements in comparison with their independent reconstruction.

1-1- Related work

Distributed algorithms for solving multiple sparse signal reconstruction problem generally divided into two categories: centralized and decentralized [7- 11]. In a centralized approach, each node runs the CS undersampling procedure independently. Then, all of the local measurements obtained from each node are collected in a fusion center (FC) which estimates the joint-sparse signals and transmits the reconstructed sparse signals back to the respective nodes. [4, 5, 6]. In contrast, in decentralized approaches, processing the measurements is performed at each node by allowing some inter-node exchange of information. In this paper, a centralized approach is proposed for joint reconstruction of sparse signals in DCS. Also, the multiple sparse signals considered in this paper belong to the type-1 joint sparse model (JSM-1), in which all of the signals are assumed to

* Corresponding Author

have a sparse common component and an innovation component [7, 8].

Recently, many DCS algorithms have been proposed for the reconstruction of signals from CS measurements in a centralized and decentralized manner. In [4] a greedy algorithm is developed for joint signal recovery, which assumes a JSM-2 model for joint sparse signals. In [12], two DCS algorithms are proposed for the VB inference problem, which introduces a distributed VB framework for conjugate-exponential models. In the first algorithm, the global parameters at each node are optimized. In the second method, the variational optimization is redefined as a constrained minimization problem with a modified objective function. In [11] a decentralized Bayesian DCS algorithm is proposed to reconstruct multiple sparse signals. This paper uses a JSM-1 model and develops the variational approximation in the Bayesian formulation to jointly reconstruct the sparse signals. In [7] a distributed greedy algorithm based on Orthogonal Matching Pursuit (OMP) is proposed for JSM-2 signal recovery. This algorithm estimates the locations of non-zero elements of the sparse signal in an iterative manner, while considering a priori knowledge of the size of the nonzero support set, which could be unknown or hard to estimate.

Distributed recovery algorithms have been efficiently studied in many CS applications that allow joint reconstruction of multiple sparse signals. For example, in [13-15], DCS have been applied to the wireless sensor networks (WSNs), where each sensor performs its measurements independently, and then, DCS develops an algorithm for the reconstruction problem, performing most of the computations in the joint decoder, which can reduce the computational complexity and energy consumption. Also, a novel video coding framework is proposed based on DCS [16-18], in which video frames are classified as CS-frames and K-frames and encode the frames using CS. Another application of the DCS theory is image fusion methods [19-21], where two or more images of the same situation combine and constitute an image which is appropriate for practical applications. A suitable fusion of visible and infrared images can obtain a precise, reliable and proper exposition of the environmental conditions. In [22], a multi-channel SAR system based on DCS has been proposed, which exploits the coherence among multiple channels, in addition to the sparsity of each channel. The joint processing requires a reduced number of samples than the multi-channel SAR imaging system based on traditional CS. Except the above-mentioned applications, there are many other application domains for DCS including: MIMO channel [23], speech enhancement (SE) [24], multichannel electroencephalogram (EEG) [25], joint channel estimation [26], and ground moving target indication (GMTI) [27].

1-2- Contribution

As mentioned above, any DCS algorithm must rely on a dependence model that illustrates the intra- and inter-signal correlation of the sparse signals. The main drawback of the previous algorithms is that the only assumption considered for each of the signals, is the sparsity of the individual signals and they do not enumerate the interdependency structure among the sparse signal coefficients. To address this drawback, and based on the fact that the wavelet transform of many signals is sparse [28, 29], in this paper, the discrete wavelet transform (DWT) has been used as the sparsifying basis. The main contribution of this paper is to exploit the tree-structure of wavelet coefficients in the proposed reconstruction algorithm to demonstrate the dependency among the wavelet coefficients. It has been proved that exploiting signal structure in addition to sparsity for CS, results in a decrease in the number of CS measurements [28].

In this work, Bayesian method is employed for the reconstruction of the signal from underdetermined data, which results in the wavelet-based Bayesian DCS (WB-DCS) algorithm. Furthermore, a Gaussian pdf is assumed for the sparse coefficients, and variational Bayes (VB) inference is employed to derive the posterior probabilities. Experimental results show that the proposed WB-DCS algorithm provides a superior reconstruction quality than the other state-of-the-art approaches.

The reminder of this paper is organized as follows. Section 2 briefly reviews the wavelet-based BCS. The Bayesian DCS framework and the VB inference procedure are provided in Section 3. Simulation results are reported in Section 4. Finally, conclusions are discussed in Section 5.

2- Wavelet-based Bayesian Compressive Sensing

In this section, we explain the CS recovery problem via Bayesian framework and use the DWT as the sparsifying basis. Let $x \in \mathbb{R}^{N\times 1}$ denote the original signal. The DWT of the signal x can be represented as [30]

$$x = \Psi\theta \qquad (1)$$

where $\Psi \in \mathbb{R}^{N\times N}$ is the matrix containing wavelet basis vectors as its columns, and $\theta \in \mathbb{R}^{N\times 1}$ is the vector of wavelet coefficients. The wavelet coefficients can be represented in a tree structure, in which every coefficient at scale s has four children at the next scale, and the statistical relationship among the parent and children coefficients is such that if the parent coefficient is negligible, then its children are also negligible. The statistical relationship between the wavelet coefficients can be demonstrated via the hidden Markov tree (HMT) model [28, 31, 32]. Fig.1 shows the DWT with three wavelet decomposition levels and two associated wavelet trees.

It has been proved that the wavelet transform of many signals and images have sparse representation, thus, enabling us to utilize the CS theory. The classical CS data acquisition is modeled by

$$y = D\theta + n = \sum_{i=1}^{N} \theta_i z_i d_i + n \quad (2)$$

where $y \in \mathbb{R}^{M\times 1}$ denotes the vector of CS measurements, $D \in \mathbb{R}^{M\times N}$ is the measurement matrix, $n \in \mathbb{R}^{M\times 1}$ is the measurement noise, d_i is the i'th column of D, and z_i is the support of the i'th coefficient, i.e. $z_i = 0$ (1) means that the i'th element of θ is zero (nonzero).

In this paper, the CS problem is formulated via a Bayesian perspective. Bayesian CS (BCS) aims to estimate the sparse coefficients vector θ from measurements y via considering a suitable pdf for hidden variables [33]. Let the measurement noise n has a zero-mean Gaussian prior distribution with precision (inverse variance) α_n. Then the likelihood function is given by

$$p(y|\theta, z) = \mathcal{N}(D\theta\, , \alpha_n^{-1} I_N) \quad (3)$$

where $I_N \in \mathbb{R}^{M\times N}$ is an identity matrix. In this work, a zero-mean Gaussian distribution is assumed for the wavelet coefficients

$$p(\theta) = \prod_{i=1}^{N} p(\theta_i^s) \qquad p(\theta_i^s) = \mathcal{N}(0\, , \alpha_s^{-1}) \quad (4)$$

where θ_i^s is the i'th component of sparse signal θ, which is at scale s, and α_s is the precision of the pdf, which is assumed to be common for all coefficients at scale s. In the next section, proposed JSM-1 DCS algorithm, namely WB-DCS, is introduced and present the prior distributions for other variables.

3- Distributed Compressive Sensing Model

In this section, we extend the BCS procedure explained in the previous section and present the proposed WB-DCS algorithm for joint reconstruction of multiple correlated signals. Also, the interactions of multiple signals is modeled via JSM-1 DCS model.

Suppose that the network has K nodes and can be modeled by an undirected graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, where $\mathcal{V} = \{1, \dots, K\}$ is the set of nodes and $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$ is the set of undirected edges that characterizes the links between the nodes. In a particular graph, there is a link between two nodes if they are neighbors. Fig. 2 shows an example graph with 7 nodes.

The CS measurements for each node is given as

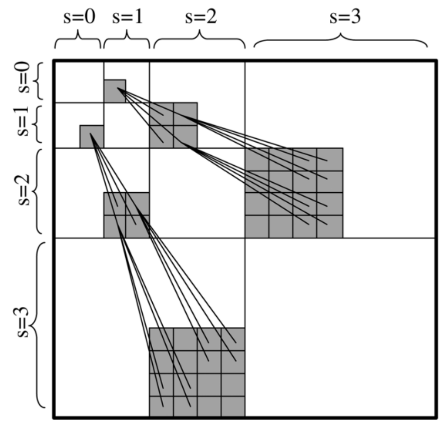


Fig. 1 The HMT structure of wavelet coefficients. [28]

$$y_k = D_k\theta_k + n_k \qquad k = 1, \dots, K \quad (5)$$

where $y_k \in \mathbb{R}^{M_k\times 1}$, $D_k \in \mathbb{R}^{M_k\times N}$, $\theta_k \in \mathbb{R}^{N\times 1}$, $n_k \in \mathbb{R}^{M_k\times 1}$ denote the measurement vector, sensing matrix, sparse signal, and noise for k'th signal, respectively, and K is the total number of signals. According to the JSM-1 DCS model, the sparse signal θ_k can be represented as

$$\theta_k = w_c \odot z_c + w_k \odot z_k \qquad k = 1, \dots, K \quad (6)$$

where $w_c \in \mathbb{R}^{N\times 1}$ denotes the common component of the sparse signal, $z_c \in \{0,1\}^{N\times 1}$ is the support vector of w_c, $w_k \in \mathbb{R}^{N\times 1}$ is the innovation component of the θ_k, which is specific to the k'th signal, $z_k \in \{0,1\}^{N\times 1}$ is the support vector of w_k, and $\odot$ denotes the Hadamard product.

In this paper, a zero-mean Gaussian distributions is assumed for the innovation and common components. Also, for modeling the elements of common and innovation supports, z_c and z_k, a HMT model is imposed in a statistical manner. Hence, the priors are given as

$$p(w_k) = \mathcal{N}(0\, , \Gamma_k) \quad (7)$$

$$p(w_c) = \mathcal{N}(0\, , \Gamma_c) \quad (8)$$

$$p(z_{k,s,i}) = Bernoulli(\pi_{k,s,i}) \quad (9)$$

$$p(z_{c,s,i}) = Bernoulli(\pi_{c,s,i}) \quad (10)$$

$$\pi_{k,s,i} = \begin{cases} \pi_{k,s} & s = 0,1 \\ \pi_{k,s0} & 2 \le s \le L, z_{pa(k,s,i)} = 0 \\ \pi_{k,s1} & 2 \le s \le L, z_{pa(k,s,i)} = 1 \end{cases} \quad (11)$$

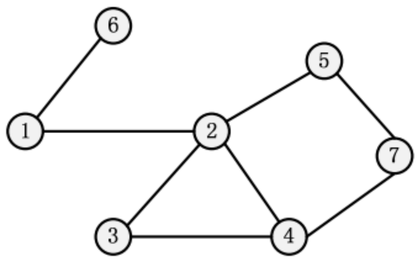


Fig. 2 A typical network structure with 7 nodes.

$$\pi_{c,s,i} = \begin{cases} \pi_{c,s} & s = 0,1 \\ \pi_{c,s0} & 2 \leq s \leq L, z_{pa(c,s,i)} = 0 \\ \pi_{c,s1} & 2 \leq s \leq L, z_{pa(c,s,i)} = 1 \end{cases} \quad (12)$$

$$p(\alpha_n) = Gamma(a_0, b_0) \quad (13)$$

$$p(\pi_{k,s}) = Beta(e_{k,s}, f_{k,s}) \qquad s = 0,1 \quad (14)$$

$$p(\pi_{k,s0}) = Beta(e_{k,s0}, f_{k,s0}) \qquad s = 2, \dots, L \quad (15)$$

$$p(\pi_{k,s1}) = Beta(e_{k,s1}, f_{k,s1}) \qquad s = 2, \dots, L \quad (16)$$

$$p(\pi_{c,s}) = Beta(e_{c,s}, f_{c,s}) \qquad s = 0,1 \quad (17)$$

$$p(\pi_{c,s0}) = Beta(e_{c,s0}, f_{c,s0}) \qquad s = 2, \dots, L \quad (18)$$

$$p(\pi_{c,s1}) = Beta(e_{c,s1}, f_{c,s1}) \qquad s = 2, \dots, L \quad (19)$$

where $\Gamma_k \in \mathbb{R}^{N\times N}$ and $\Gamma_c \in \mathbb{R}^{N\times N}$ are diagonal matrices whose elements are the precisions $\alpha_{k,s}$ and $\alpha_{c,s}$, respectively, (k,s,i) and (c,s,i) denote the index of i'th element at scale s which belongs to the k'th innovation component and the common component, respectively, $\pi_{k,s,i}$ and $\pi_{c,s,i}$ denote the mixing weights adopting Beta priors with the specified hyperparameters, $z_{pa(k,s,i)}$ and $z_{pa(c,s,i)}$ denote the support of the parent coefficient of $w_{(k,s,i)}$ and $w_{(c,s,i)}$, respectively, and L is the total number of wavelet decomposition levels.

3-1- Variational Bayes Inference

To solve the joint recovery problem and infer the posterior distributions of the proposed WB-DCS algorithm, VB inference is implemented. The fundament of VB inference is to provide an estimate of the true posterior distribution $p(.)$, say $q(.)$, by adopting a factorable distribution [34]. For simplicity, define $Y = \{y_1, \dots, y_K\}$, $W = \{w_c, w_1, \dots, w_K\}$, $Z = \{z_c, z_1, \dots, z_K\}$ and $\theta = \{\Gamma_c, \Gamma_1, \dots, \Gamma_K, \pi_c, \pi_1, \dots, \pi_K, \alpha_n\}$. Assume that the $q(W)$ and $q(Z)$ can be factorized as

$$q(W) = q(w_c)q(w_1)\dots q(w_K) \quad (20)$$

$$q(Z) = q(z_c)q(z_1)\dots q(z_K) \quad (21)$$

Then, based on the priors presented in the previous section, the estimated posterior distributions $q(w_c)$ and $q(w_k)$ at each iteration are given by

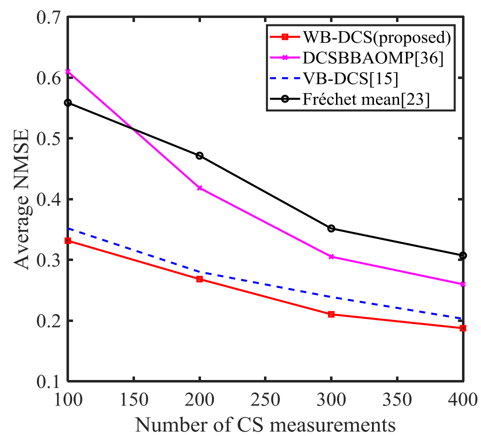


Fig. 3 Comparison of the normalized mean square error for the temperature signals.

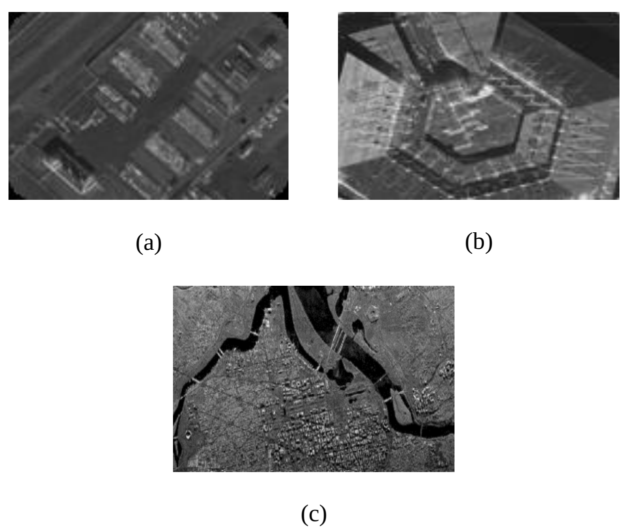


Fig. 4 3-D SAR images downloaded from [38].

$$q(w_c) \propto \exp(\mathbb{E}_{q(w_1),\ldots,q(w_K)}[\ln p(y_1, \ldots, y_K, w_c, w_1, \ldots, w_K, z_c, z_1, \ldots, z_K; \Gamma_c, \Gamma_1, \ldots, \Gamma_K, \pi_c, \pi_1, \ldots, \pi_K, \alpha_n)])$$

$$\propto \exp(\mathbb{E}_{q(w_1)}[\ln p(y_1|w_c, w_1, z_c, z_1, \alpha_n) + \cdots + \ln p(y_K|w_c, w_K, z_c, z_K, \alpha_n) + \ln p(w_c|\Gamma_c)]$$

$$= \mathcal{N}(\mu_c, \Sigma_c) \tag{22}$$

$$q(w_k) \propto \exp(\mathbb{E}_{q(w_c),q(w_j),j\neq k}[\ln p(y_1, \ldots, y_K, w_c, w_1, \ldots, w_K, z_c, z_1, \ldots, z_K; \Gamma_c, \Gamma_1, \ldots, \Gamma_K, \pi_c, \pi_1, \ldots, \pi_K, \alpha_n)])$$

$$\propto \exp(\mathbb{E}_{q(w_c)}[\ln p(y_k|w_c, w_k, z_c, z_k, \alpha_n) + \ln p(w_k|\Gamma_k)]$$

$$= \mathcal{N}(\mu_k, \Sigma_k) \tag{23}$$

where

$$\mu_c = \alpha_n \Sigma_c Z_c{}^T (\textstyle\sum_{k=1}^{K} \{D_k^T (y_k - D_k Z_k \mu_k)\}) \tag{24}$$

$$\Sigma_c = \{\Gamma_c^{-1} + \alpha_n Z_c{}^T (\textstyle\sum_{k=1}^{K} D_k^T D_k) Z_c\}^{-1} \tag{25}$$

$$\mu_k = \alpha_n \Sigma_k Z_k^T D_k^T (y_k - D_k Z_c \mu_c) \tag{26}$$

$$\Sigma_k = (\alpha_n Z_k^T D_k^T D_k Z_k + \Gamma_k^{-1})^{-1} \tag{27}$$

where $Z_{(.)} = diag(z_{(.)})$. According to the Eqs. (22) and (23), it can be authenticated that $q(w_c)$ and $q(w_k)$ are Gaussian distributions. Applying similar process for other hidden variables, where $q(w_c)$ and $q(w_k)$ are given, approximate posterior distributions are obtained as follows:

$$q(z_{k,s,i}) \propto p(z_{k,i}) \sqrt{\Sigma_{k,i}}\, exp\left(-\frac{1}{2}\frac{\mu_{k,i}^2}{\Sigma_{k,i}}\right) \tag{28}$$

$$q(z_{c,s,i}) \propto p(z_{c,i}) \sqrt{\Sigma_{c,i}}\, exp\left(-\frac{1}{2}\frac{\mu_{c,i}^2}{\Sigma_{c,i}}\right) \tag{29}$$

$$q(\alpha_n) = Gamma(a_0', b_0') \tag{30}$$

$$q(\pi_k) = \prod_{s=0}^{1} Beta(e_{k,s}', f_{k,s}') \times \prod_{s=2}^{L} Beta(e_{k,s0}', f_{k,s0}') Beta(e_{k,s1}', f_{k,s1}') \tag{31}$$

$$q(\pi_c) = \prod_{s=0}^{1} Beta(e_{c,s}', f_{c,s}') \times \prod_{s=2}^{L} Beta(e_{c,s0}', f_{c,s0}') Beta(e_{c,s1}', f_{c,s1}') \tag{32}$$

$$q(\alpha_{k,s}) = Gamma(c_0', d_0') \tag{33}$$

$$q(\alpha_{c,s}) = Gamma(e_0', f_0') \tag{34}$$

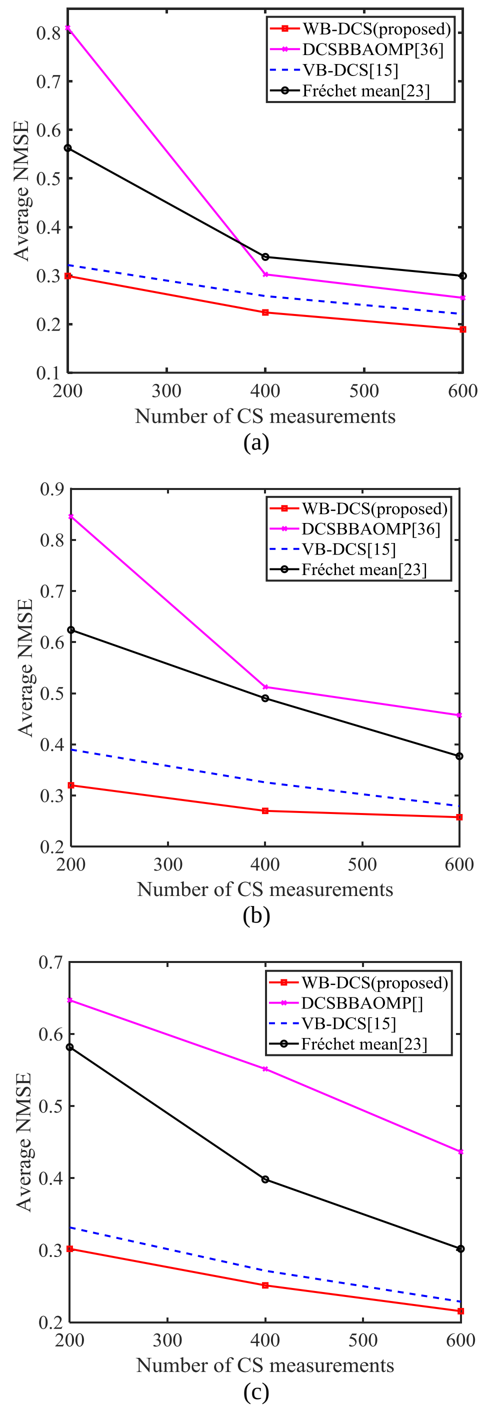


Fig. 5 Comparison of the normalized mean square error for the SAR images of Fig. 4.

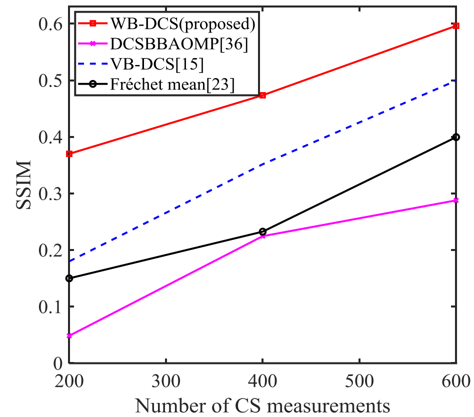
where $a_0' = a_0 + \frac{KM}{2}$ and $b_0' = b_0 + \frac{1}{2}\sum_{k=1}^{K}\|y_k - D_k\theta_k\|_2^2$. The variational optimization procedure iteratively updates until convergence occurs to stable hyperparameters. Finally, the reconstructed signal can be obtained as

$$\theta_k = \mu_c \odot z_c + \mu_k \odot z_k \quad (35)$$

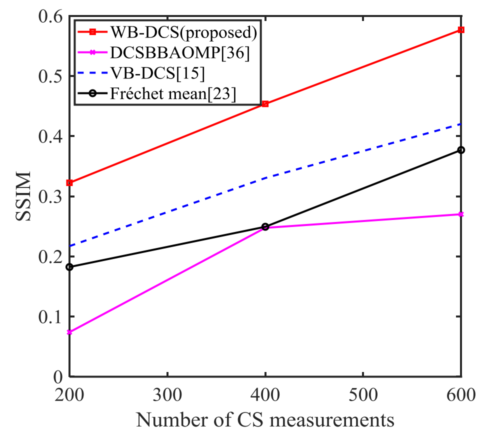
4- Simulation Results

In this section, the performance of the proposed centralized WB-DCS algorithm in two settings is evaluated. First, the experiments are tested for the 1-D temperature signals. In the second scenario, the efficiency of the proposed algorithm is investigated for the 3-D SAR images. The results of the proposed algorithm and that of three recent algorithms presented for DCS signal reconstruction are compared: the centralized part of the Bayesian DCS algorithm proposed in [11], the centralized Fréchet mean approach [35], and the backtracking-based adaptive orthogonal matching pursuit for block distributed compressed sensing (DCSBBAOMP) algorithm proposed in [36]. All of the competing algorithms assume JSM-1 model for the signals and exploit both the intra- and inter-signal dependencies. The centralized algorithm used in [11] is a Bayesian DCS algorithm and estimates the jointly sparse signals based on the VB inference procedure. The Fréchet mean approach is also a centralized algorithm, but the effect of innovation components in the reconstruction of common component is ignored. The DCSBBAOMP algorithm reconstructs block-sparse signals in an iterative manner, which each iteration consists of forward selection and backward removal stages.

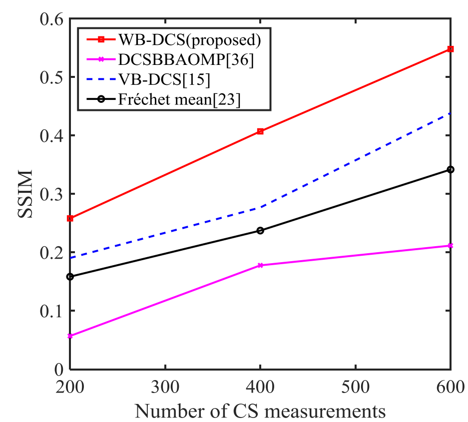
In the following evaluations, the DWT is used as the sparsifying transform, and the elements of all the sensing matrices D_k are i.i.d and drawn randomly from a zero-mean Gaussian distribution with variance $\frac{1}{M}$. The sparsifying domain used in [11] is the discrete cosine transform (DCT), and the sensing matrices are random partial DCT matrices. For fair comparison, the same settings is used in all simulations, i.e. the curves presented as the results of [11] are based on the sparse coefficients obtained by the DWT transform and Gaussian measurement matrices. Also, parameter setting for the DCSBBAOMP algorithm is the same as [36].



(a)



(b)



(c)

Fig. 6 Comparison of the structural similarity index for the SAR images of Fig. 4.

4-1- Experiments with 1-D Signals

In this subsection, the algorithms mentioned above are tested for the 1-D temperature signals downloaded from the Intel Berkeley Research lab [37]. A set of $K = 10$ temperature signals of length $N = 512$ is considered and in the recovery process, this signals are jointly reconstructed in an iterative manner. The comparison of competing algorithms is in terms of normalized mean square error (NMSE), $NMSE(x) = 10 \log\left(\frac{\|x-\hat{x}\|_2^2}{\|x\|_2^2}\right)$, where x and $\hat{x}$ denote the original and the reconstructed signal, respectively. For each experiment setting, 100 trials are implemented and the averaged result are provided.

The average NMSE results of the reconstructed temperature images are displayed in Fig. 3. It is seen that the proposed WB-DCS algorithm, which exploits the structure of wavelet coefficients, has better performance than the other algorithms in terms of NMSE, where they only assumption is the intra- and inter-signal correlations of the signals.

4-2- Experiments with 3-D Signals

In the following set of experiments, the algorithms mentioned above are compared for 3-D SAR images. Three SAR images are selected, which are downloaded from Sandia National Laboratories in U.S. [38] and shown in Fig. 4. All simulations are for 32×32 images. For all competing algorithms, two quality assessors are used to compare the results: (1) NMSE, and (2) structural similarity (SSIM) [39], which evaluates the similarity between the original and the reconstructed image. The SSIM index is defined as $SSIM(\boldsymbol{x}, \hat{\boldsymbol{x}}) = \frac{(2\mu_x\mu_{\hat{x}}+C_1)(2\sigma_{x\hat{x}}+C_2)}{(\mu_x^2+\mu_{\hat{x}}^2+C_1)(\sigma_x^2+\sigma_{\hat{x}}^2+C_2)}$, where $\mu_{(.)}$ is the mean intensity, $\sigma_{(.,.)}$ is the covariance, $\sigma_{(.)}^2$ is the variance, and C_1 and C_2 are some constants.

The utilization of the DCS algorithm for each SAR image, exploits structural dependencies between adjacent azimuth–range pixels and/or polarimetric channels [40].

Fig. 5 depicts the NMSE results versus the number of experiments for the SAR images of Fig. 3. Each point is based on the average of 100 trials. It can be seen that the proposed method obtains the lowest reconstruction error among all the other competing algorithms.

A SSIM comparison between the proposed WB-DCS algorithm and the competitive methods is illustrated in

Fig. 6. Based on this results, it can be demonstrated that the use of a profitable model for enumerating the inter-scale, intra- and inter-signal dependencies of jointly sparse signals, simultaneously, leads to an improvement in DCS signal recovery in terms of SSIM, such that the highest SSIM is obtained by the proposed algorithm.

5- Conclusion

In this paper, a centralized wavelet-based Bayesian DCS algorithm (WB-DCS) is proposed to jointly reconstruct multiple signals. Both the inter- and intra-signal correlations are exploited by the JSM-1 DCS model. Furthermore, the DWT is used as sparsifying transform and the HMT model is employed to demonstrate the inter-scale structure associated with wavelet coefficients. Also, this correlation is statistically employed within a Bayesian prior, and the posteriors of unknown variables are estimated using the VB inference procedure. Experimental results confirmed that the proposed WB-DCS algorithm significantly outperforms the state-of-the-art DCS recovery algorithms in terms of reconstruction error and structural similarity index (SSIM). Future research includes exploiting approximate message passing algorithm for the recovery process, which can help significantly reduce the computational complexity of Bayesian inference. Also, in addition to the sparsity and the local structure of the sparse signals considered in this work, we would like to exploit the nonlocal self-similarity of images in our future work, which represents the repetitive behavior of the higher level patterns globally located in the images.

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Razieh Torkamani received the B.S. and M.S. degrees from the Iran University of Science and Technology (IUST), Tehran, Iran, in 2010 and 2012, respectively. She is currently working toward the Ph.D. degree in the faculty of Electrical Engineering and Computer Science, in the K.N. Toosi University of Technology. Her research interests include compressive sensing and recovery algorithms, statistical signal processing, sparse signal representations, and graphical models.

Professor R.A. Sadeghzadeh is a full professor of Communications Engineering at the faculty of Electrical Engineering of the K.N. Toosi University of Technology in Tehran, Iran. He received his B.Sc. in 1984 in telecommunication Engineering from the K.N. Toosi, University of Technology and M.Sc. in Digital Communications Engineering from the University of Bradford and UMIST (University of Manchester Institute of Science and Technology), UK as a joint program in 1987. He received his Ph.D. in electromagnetic and antenna from the University of Bradford, UK in 1990. Professor Sadeghzadeh worked as a Post-Doctoral Research assistant in the field of propagation, electromagnetic, antenna , Bio-Medical, and Wireless communications from 1990 till 1997 at the University of Bradford, UK. From 1984 to 1985 he was with Telecommunication Company of Iran (TCI) working on Networking. Since 1997 He is with the K.N. Toosi University of Technology working with Telecommunications Department at the faculty of Electrical Engineering. He has published more than 200 referable papers in international journals and conferences. Professor Sadeghzadeh current interests are numerical techniques in electromagnetic, antenna, propagation, radio networks, wireless communications, nano-antennas and radar systems.