Resource Redistribution in Internet of Things applications by Compressed Sensing: a Survey

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***Abstract*—The incoming Internet of Things revolution requires the adoption of innovative paradigms for the design of low-power ubiquitous sensor nodes. This can be achieved by exploiting Compressed Sensing (CS), that is a recently introduced approach capable of simultaneously sampling and compressing an input signal with a limited amount of resources. While the underlying basic theory is well developed, in recent years we have seen a flourishing of CS techniques capable of exploiting some additional priors on the input signal to improve performance. In this paper, we propose a survey and a comparison of the most promising ones. We use a classification mechanism based on which prior is used and which processing block is modified with respect to the standard CS.**

I. Introduction

Internet of Things (IoT) is emerging as a promising and revolutionary paradigm in Information and Communication Technology related tasks [1]. Based on the collection and processing of large amounts of data from a number of interconnected sensor nodes, the IoT paradigm relies on the development of low-cost, low-energy data acquisition nodes, typically communicating with a central gateway by means of a Wireless Sensor Network (WSN). According to this point of view, low energy consumption and high communication capacity will be fundamental properties of any sensing node.

As already pointed out by some contributions in the literature [2]–[5], standard approaches applied to the forthcoming sensing nodes show many limitations. The situation is illustrated in Fig. 1, showing the amount of resources required by different approaches. A simple and straightforward transmission of uncompressed Nyquist rate symbols may be unacceptable due to the inefficient use of the transmission channel capacity. Conversely, the adoption of a compression technique at the sensor node exploiting spatial and/or temporal correlation of the input signal to reduce the amount of transmitted data may require algorithms that are out of budget, either in terms of hardware complexity or energetic cost. A possible workaround for this situation is represented by the recently introduced Compressed Sensing (CS) paradigm [6]. Under some assumptions on the input signal, CS is capable to perform a sub-Nyquist sampling, (i.e., a simultaneous acquisition and compression process) with a surprisingly simple mechanism (projection of the input signal on a set of typically random sampling waveforms). In this way, as illustrated in Fig. 1, it is possible to lower both sensing node energy and channel capacity requirements, at the cost of an increased complexity of the recovery stage [7]. In other words, CS works as a *resource redistribution* technique between encoding and decoding stage. Note that this is an important advantage in the WSN-based IoT, since the energetic budget at an IoT collector is typically much higher with respect to that available at a sensor node.

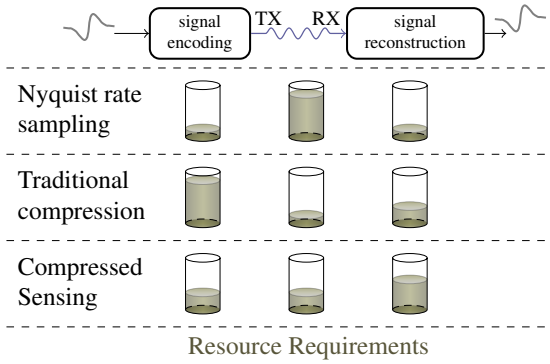

Fig. 1. Comparison between resources required by Nyquist rate sampling (large transmission channel capacity required), traditional compression (high encoder resources required) and Compressed Sensing (resources are balanced, with predominant decoder requirements).

The aim of this paper is to provide a survey and a comparison of advanced CS techniques that could reduce requirements at the sensor node by fostering the resource redistribution between encoding and decoding stage. All these techniques are capable of exploiting additional input signal priors either to improve CS performance at given resources budget, or to lower resource requirement to achieve a target performance level. We will also propose a classification of these techniques according to the signal prior that is used, and to the signal processing block that is modified with respect to standard CS approach. This will help readers to understand the differences and to evaluate the proposed techniques.

The paper is organized as follows. In Section II a brief introduction on the CS is provided. Section III provides an overview of recently proposed CS optimization techniques, organized in three different groups depending on which part of the system is modified with respect to the standard CS approach. Finally, we draw the conclusion.

II. CS Fundamentals

The working principle of CS is illustrated in Fig. 2. Basically, an input signal x with intrinsic dimension n (i.e., x has n degrees of freedom) is *encoded* into a vector of measurement with dimension $m < n$, that is dispatched to a *decoder* whose aim is to reconstruct $\hat{x}$ as the best approximation of x. CS can

be applied either to signals that are instances of a continuous time or discrete time process. For the sake of simplicity, we focus on the latter, and define a signal instance $x \in \mathbb{R}^n$ according to its n Nyquist rate samples.

CS is effective under the assumption that input signal is κ-sparse, i.e., that a proper orthonormal n-dimensional *sparsity basis* $S \in \mathbb{R}^{n \times n}$ exists, along which any instance $x = S\xi$ is such that $\xi \in \mathbb{R}^n$ has no more than $\kappa \ll n$ non-zero components. The set Ξ of the κ non-zero components of ξ is referred to as the *support* of the signal.

Then, *encoding* is achieved by linearly projecting x over a sensing matrix $A \in \mathbb{R}^{m \times n}$

$$y = Ax + \nu = B\xi + \nu \tag{1}$$

where $B = AS$ is the matrix mapping the sparse representation ξ into the vector $y \in \mathbb{R}^m$ made with the m measurements, and ν is an additive disturbance term used to model non-idealities such as the quantization error or the signal noise. We define the compression ratio provided by the CS encoder as $CR = n/m$.

Finally, *decoding* is ensured given some properties on A and a minimum number of measurements

$$m \geq C\kappa \log_{10}\left(\frac{n}{\kappa}\right) \tag{2}$$

where C is a constant whose value is commonly set around 5 [8].

Mathematically, $\hat{x} = S\hat{\xi}$, where $\hat{\xi}$ is found by looking for vectors ξ that solve (1) with a proper tolerance. Being an ill-posed problem, multiple solutions exist; a classical result [7] states that the correct one is the sparsest one given by the constrained optimization problem

$$\hat{\xi} = \arg\min_{\xi} \|\xi\|_1 \quad \text{s.t. } \|B\xi - y\|_2 < \varepsilon \tag{3}$$

where $\|\cdot\|_p$ is the standard ℓ_p norm and ε bounds the effects of ν. Such an approach is called basis pursuit with denoising (BPDN), and can be shown to be equivalent to the unconstrained problem

$$\hat{\xi} = \arg\min_{\xi} \left(\frac{1}{2}\|B\xi - y\|_2 + \lambda\|\xi\|_1\right) \tag{4}$$

for a proper value of the parameter λ.

Two properties of A guarantee correct reconstruction: i) the *restricted isometry* property (RIP), i.e., A is able to approximately preserve the signal energy as $\|Ax\|_2 \approx \alpha\|x\|_2$ for some constant α as close as possible to 1 and for all κ-sparse vectors x; and ii) the *low-coherence* property, where coherence is defined as follows

$$\mu(A, S) = \sup_{j,k} |\langle A_{j,\cdot}, S_{\cdot,k} \rangle| \tag{5}$$

where $A_{j,\cdot}$ is the j-th row of A and $S_{\cdot,k}$ is the k-th column of S.

The adoption of either Gaussian or Sub-Gaussian random sensing matrices ensures both properties and provides upper bounds on the reconstruction error $\|x - \hat{x}\|_2$, that is usually defined except for a positive constant. These bounds are based on both coherence (for the noiseless case, i.e., $\nu = 0$) and on RIP (for noisy case) [7].

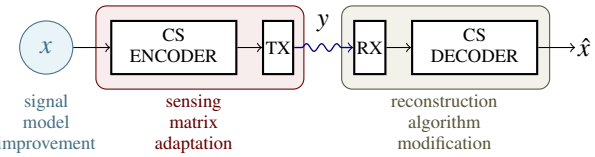

Fig. 2. Block scheme of the CS processing chain, along with the proposed classification mechanism of the considered optimization techniques.

III. Improving CS by using Additional Priors

Many circuital solutions have been proposed to reduce energy requirements in a CS-based sensor node [9]–[12]. As an example, limiting $A_{j,k} \in \{-1, 1\}$ or $A_{j,k} \in \{-1, 0, 1\}$ reduces both hardware complexity and energy necessary for the encoding [13] with almost no performance loss [8].

Here we are interested not in circuit-related solutions, but in approaches that can improve performance using additional signal priors independently of the CS implementation. As an example, according to standard CS theory, (2) represents the optimum value of m in the sense that without any additional knowledge on the acquired class of signals there is no alternative method to design A that ensures better reconstruction performance.

However, given a class of input signals, this approach is completely nonadaptive, and performance could not correspond to the required minimum level. A first step in this direction was presented in [14], [15], with guidelines in the design of a sensing matrix that, for a given S, is capable to reduce $\mu(A, S)$ and thus the value of m required for a correct reconstruction. These methods, exploiting only the knowledge of S, have a limited impact on the overall system performance with respect to other methods that work with additional priors as, for example, second order statistic or structural sparsity. In the following, we propose a review of the latter approaches, organizing them in three categories depending on which part of the system is modified with respect to the standard CS approach. Classification is also illustrated in Fig. 2, while a high-level comparison of considered approaches is reported in Tab. I.

A. Signal model improvement

As first class of CS approaches, we refer to methods based on a different signal model. In [16]–[19] the signal of interest is supposed to be *block-sparse*, i.e., signal instances are still sparse and non-null elements of ξ are grouped in few blocks.

As an example, in [19] electrocardiogram signals (ECG) are considered as chunks of non-null signals (in case of peaks) followed by pieces of signals that are approximately zero. As a case study, authors discuss the impact of CS in the design of a Fetal ECG (FECG) tele-monitoring device, where the main part of the desired information is hidden among mother ECG details. For this task standard CS typically fails, since the entire CS framework aims to recover the highest entries in ξ only.

Nevertheless, this is the case where the adoption of a block sparse signal along with a Bayesian learning framework, makes FECG encoding/decoding by CS effective. In particular, each block of non-null entries is modeled as a multivariate random Gaussian variable such that the reconstruction algorithm performs recovery by estimating the current instances of

these random multivariate variables by means of the Block-Sparse Bayesian Learning algorithm (BSBL). To prove the effectiveness of this method, authors extract the FECG from the raw mother ECG, and compare it with that obtained from the reconstructed mother ECG using the BSBL algorithm. The two extracted FECGs are almost identical, with a Pearson correlation equal to 0.931.

Another research branch focuses on WSN applications where the signal x could be sparse with respect to both spatial and temporal representations [2], [5]. In particular, the approach presented in [2] proposes a WSN data acquisition whose aim is to monitor a multi source phenomena such as the temperature inside a sensing area, and based on the knowledge that most nodes keep a sleeping operation mode with a predefined mechanism. This additional prior, addressed as *signal discontinuity*, could be used in the design of A and in the recovery mechanism.

The input vector x contains data from all sensors at a given time that are transmitted to a number of gateways, each of them monitoring a sub-network and further relying the data to a central aggregator by means of long-range communications. This system model is mapped in the sensing matrix considering that: i) the i-th gateway compresses data from sensors in its neighborhood into m_i rows of A in order to compute a subset of the entire measurement vector y where $\sum_{i=1}^{M} m_i = m$ and M is the number of gateways; ii) only a subset of the nodes in a neighborhood are active, i.e., the corresponding elements of x are not null. For these reasons, the m_i rows of A associated to the i-th gateway have zeros in all columns associated to sensors outside its neighborhoods, as well as in the columns associated to inactive sensors. All other matrix entries in the same rows are randomly drawn in accordance to standard CS. Therefore, the entire matrix A has a set of structured zeros related to the positions of nodes and gateways and zero entries changing dynamically in accordance to the adopted policy in the sensors activation.

The authors of [2] propose also a new decoding approach based on this signal model that is able to outperform others more common approaches used in CS decoding as, for example, the CoSaMP algorithm [20]. This new decoding algorithm is named Adaptive Cluster Sparse Reconstruction Algorithm (ACSRA). Authors also show with a practical example that the proposed framework decreases the communication load over the network by approximately 80%.

B. Sensing matrix adaptation

In the second class of CS approaches we consider, the design of A is tuned according to some properties of x. This is the case of [3], [21] where A is changed in a very simple way. These methods, by a continuous monitoring of the sparsity level of the reconstructed signals, exploit a feedback from the decoder to the encoder to adapt the CR value and thus to dynamically change the number of rows in A.

An even more interesting approach is the focus of [22]–[24] known as *adaptive sensing*, where one of the main CS general assumptions is broken, i.e., a dependency between successive rows of A is introduced. In particular, [23] investigates the case where the rows of A are constrained to be part of a predefined set (the *constrained adaptive sensing*). As an example, in magnetic resonance imaging, the encoder limits itself to compute measurements by projecting the input signal on vectors of the Fourier basis.

The underlying idea is that rows of A properly selected over a predefined set are able to outperform a purely random selection in terms of minimum reconstruction error. As main prior, an estimation of the current signal support Ξ is provided such that the reconstruction error can be written as

$$\mathbf{E}[\|x - \hat{x}\|_2^2] = \|(AS_\Xi)^\dagger\|_F^2 \, \sigma^2 = \mathrm{tr}\left(\left((AS_\Xi)^* \, AS_\Xi\right)^{-1}\right) \sigma^2$$

where $\mathbf{E}[\cdot]$ stands for expectation, S_Ξ is S limited to the columns corresponding to the support Ξ, $\|\cdot\|_F$ is the Frobenius matrix norm, $\cdot^\dagger$ is the Moore-Penrose pseudoinverse and σ^2 represents the variance of the noise term in (1).

Let us indicate with $\tilde{A} \in \mathbb{R}^{n \times n}$ the transpose of the matrix with all possible sensing waveforms, and with P a diagonal matrix whose elements $P_{j,j} = 1$ if the j-th row of $\tilde{A}$ is selected to compose A, and 0 otherwise. The authors of [23] say that error reconstruction is minimized if such a selection follows the solution of the optimization problem

$$\min_{\text{diag. mat. } P} \mathrm{tr}\left(((\tilde{A}S_\Xi)^* P A S_\Xi)^{-1}\right) \quad \text{s.t.}\, \mathrm{tr}(P) \leq m$$

where $\mathrm{tr}(\cdot)$ stands for matrix trace.

In a case study, the authors devote $m/2$ measurement, obtained in accordance to the standard CS, in order to estimate Ξ while the remaining measurement are obtained by applying the above method. Simulations with signals sparse on the Haar wavelet basis and $\tilde{A}^\top$ as the Fourier basis show that this method is able to strongly reduce the reconstruction error with respect to the case where sensing vectors are randomly chosen.

A different framework has been introduced in [25], with applications in [26]–[30], known as *rakeness*-based CS. Here the main difference with respect to standard CS is the use of a proper correlation profile for the symbols composing each row of A while independence between rows is still preserved.

The exploited prior is the second order statistic of the input signals, i.e., an estimation of the signal correlation matrix $\mathcal{X} = \mathbf{E}[xx^\top]$. Such matrix can be analyzed to assess how much the process generating signal instances deviates from a purely random process with a flat spectral profile. This deviation can be named as *localization* and could be evaluated by

$$\mathfrak{L}_x = \mathrm{tr}\left(\mathcal{X}^2\right)/\mathrm{tr}^2(\mathcal{X}) - 1/n$$

Rakeness-based CS suggests drawing the generic row a of A according to a process with correlation matrix $\mathcal{A} = \mathbf{E}_a[aa^\top]$ that is the solution of an optimization problem aiming to increase the measurement vector energy with the constraint that $\mathfrak{L}_a \leq l\mathfrak{L}_x$, where $\mathfrak{L}_a$ is the localization of the process generating rows of A and l is typically set to 0.5 [31].

Interestingly, the rakeness optimization problem in [25] can be analytically solved such that the application of the entire method uses matrices A whose rows feature the following correlations matrix

$$\mathcal{A} = e\left(\frac{\mathcal{X}}{\mathrm{tr}(\mathcal{X})}\sqrt{l} + \frac{1}{n}\boldsymbol{I}_n\left(1 - \sqrt{l}\right)\right)$$

where e is the ℓ_2 norm of each row of A. In [30] there are also definitions and methods to cope with cases where A entries are limited to be either binary, i.e., $A_{i,j} \in \{0, 1\}$ or ternary, i.e.,

$A_{i,j} \in \{-1, 0, 1\}$[1]. Results in [26]–[30], [32], for different classes of signals, show a strong reduction in terms of error reconstruction with respect to the standard CS approach. In particular, [30] provides a comparison with [19] and [33] that highlights the effectiveness of this approach.

C. Reconstruction algorithm modification

In the third class of approaches, we include solutions that focus on the decoding stage. The reconstruction problem, either in the form of (3) or (4), can be easily solved by mapping it into a linear programming problem. Based on this observation, general purpose solvers as ℓ_1-MAGIC [34] and SPG-ℓ_1 [35] have been developed.

Nevertheless, even if these solvers ensure good reconstruction performance according to the CS theory, they are computationally expensive and do not feature any specialization to a signal class. In order to reduce reconstruction costs (in terms of both time and energy), one can rely on greedy approaches that iteratively promote sparsity by means of intermediate and approximated solutions. Among the several approaches developed so far, a fast and light-weighted algorithm that is worth mentioning is OMP [36]. Despite providing only approximated solutions, all these approaches ensure a lower complexity with respect to general methods [12] and can be of paramount importance when the decoder is a battery-powered device or when n is high and the real-time constraint holds.

Some iterative reconstruction algorithms are also able to exploit input signal priors, for example, authors of [20] propose CoSaMP, that is based on the a-priori knowledge of the sparsity level κ. A similar approach is used in the light-weight IHT proposed in [37], that ensures correct signals reconstruction when κ/n is low with a very limited computational cost.

Many other approaches can be found in the literature based on other priors. For example, MU-GAMP [38] uses hypothesis on both input signal and noise statistics. Other approaches use an iterative and reweighted algorithm [39], [40]. The literature on decoding approaches is extremely flourishing [41]–[44] and a complete overview would exceed the limit of this brief survey.

We may here focus on an interesting decoding solution, the Weighted ℓ_1 Minimization (WLM) proposed in [33]. As rakeness-based CS, WLM uses signal statistic as additional prior, but in a different way. In more detail, authors make an estimation of the probability, for each column of S, to be included in the current Ξ. From these values, a diagonal matrix $W \in \mathbb{R}^{n \times n}$ is defined whose entries are the inverse of the observed frequency. The intuition is to promote reconstructed vectors $\hat{\xi}$ with a support similar to what is observed in average instead of using the straightforward solution of the reconstruction problem where each element of $\hat{\xi}$ is non-null with the same probability. To this aim, it is possible to replace (4) with the optimization problem

$$\hat{\xi} = \arg\min_{\xi} \frac{1}{2}\|B\xi - y\|_2^2 + \lambda \|W\xi\|_1$$

where the normalization parameter is set to $\lambda = 0.1$ according to authors' suggestion.

The authors of [33] focus on the ECG signal. They provide a matrix W to be used for reconstructing ECG signal when $n = 512$ and when S is the Daubechies-6 wavelet basis matrix. Simulations on real ECG tracks show how WLM reduces the reconstruction error, for a proper value of m, when compared with other decoding approach as OMP, IHT, BSBL and more.

Finally, [45] presents an innovative decoding procedure in the design of a multi-electrode neural signals acquisition system based on CS. The main characteristic of this approach is a two-step signal reconstruction. It is assumed that each instance x is composed by two contributions, x_c containing the mean shape, and x_f with waveform details. Furthermore, x_c is a 1-sparse signal over a custom dictionary D trained during an initialization phase where the system transmits raw data of the proper user, while for the κ-sparse signal x_f a Wavelet basis is considered as S.

$$x = x_c + x_f = D\xi_c + S\xi_f$$

Authors used this model to define a two-step decoding procedure that is described as follows. As first ξ_c is recovered by enforcing sparsity equal to 1.

$$\hat{\xi}_c = \arg\min_{\xi_c} \|y - AD\xi_c\|_2 \qquad \text{s.t. } \|\xi_c\|_0 = 1$$

After that a residual of the measurement vector is computed as $r = y - AD\hat{\xi}_c$ and x_f is reconstructed by

$$\hat{\xi}_f = \arg\min_{\xi_f} \|r - AS\xi_f\|_2 \qquad \text{s.t. } \|\xi_f\|_1 \leq \lambda$$

where λ is a regularization parameter that limits x_f sparsity. Finally, the reconstructed signal is $\hat{x} = D\hat{\xi}_c + S\hat{\xi}_f$.

Tests on a reference dataset highlight how this method is able to outperform standard CS in terms of both reconstruction error and spike detection or, equivalently, this approach allows to keep m to a value lower then what is needed by standard CS with the same neural spike identification capability and with the same reconstruction error.

TABLE I
CS FRAMEWORKS WITH ADDITIONAL PRIORS

Main change	Additional prior	Introduced novelty	Universality	Performance	Ref.
III-A	block sparse	new decoder	●	●●●	[16]–[19]
	signal discontinuity	new decoder	●●	●●	[2]
III-B	signal support	new encoder	●●	●●	[23]
	signal statistic	new encoder	●●●	●●●	[25]–[30]
III-C	signal statistics	new decoder	●●●	●●	[33]
	signal decomposition	new decoder	●	●●●	[45]

IV. Conclusion

In this paper, a survey of innovative CS technique for improving system performance exploiting input signal priors is presented. These techniques have been divided into three groups according to the processing block that has been modified with respect to the standard CS approach. The used prior is also identified to help readers to understand the differences and to evaluate the proposed techniques.

[1]Matlab implementation avaliable at *http://cs.signalprocessing.it*

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