

# Review on One-Bit Compressive Sensing and its Biomedical Applications

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**Abstract**—As a specific class of compressive sensing, one-bit compressive sensing can use sign measurements (one-bit information) to recover sparse signals. One-bit information can be sampled in a very high rate with a relatively low cost. The progress of 1bit-CS, including models, algorithms, and applications, is reviewed in this paper. Additionally, mixed one-bit compressive sensing, which can deal with analog and sign measurements simultaneously, is introduced together with an experiment on computed tomography for a phantom.

**Index Terms**—one-bit compressive sensing; Mixed One-bit Compressive Sensing; reconstruction algorithm

## I. INTRODUCTION

The traditional sampling system, based on the Nyquist sampling theorem, requires a sampling rate of at least twice the bandwidth. Then for signal in a wide bandwidth, a high sampling rate is required and a large amount of data are sampled. Since 2005, Candès, Donoho, Tao et al. put forward the theory of Compressive Sensing (CS, [1], [2]), with which it is now possible to reconstruct sparse or compressible signal with a sub-Nyquist rate. Since in many applications, the underlying signals are indeed sparse, CS has gained extensive interest and development since its proposal.

The original CS model assumes the measurements to be real-valued. However, in practice systems, measurements are always quantized by Analog to Digital Converter (ADC). And discussions raised for the signal recovery performance with different digit depth and different sampling rate [3]. In [4], an extreme case that there is only one bit for each measurement is discussed and the so-called One-bit Compressive Sensing (1bit-CS) is proposed. Since the use of one-bit measurements allows high sampling rate, low power consumption, and small measurement storage [5], [6], [7], 1bit-CS has attracted much research interests and has been widely applied in fields, such as wireless sensor networks and radar signal processing, where reduction on the amount of data and sampling rate is preferred.

This paper aims to provide the reader with a literature review of 1bit-CS, which is rarely mentioned by reviews of regular CS. Particularly, we additionally introduce a recently proposed method called Mixed One-bit Compressed Sensing (M1bit-CS), which is between regular CS and 1bit-CS. M1bit-CS is suitable to deal with both analog and one-bit measure-

ments. A direct biomedical application of M1bit-CS is on image reconstruction for computed tomography (CT).

The rest of this paper is organized as follows. Section II introduces the basic model of 1bit-CS; Section III reviews several efficient algorithms for 1bit-CS and also introduces M1bit-CS. The applications of 1bit-CS and M1bit-CS are discussed in Section IV; Section V shows the application of M1bit-CS on CT reconstruction. Brief conclusions and future prospects are given in Section VI to end this review.

## II. COMPRESSIVE SENSING AND ONE-BIT MODIFICATION

### A. Compressive Sensing (CS)

In a linear sensing system, the task is to recover original signal  $\mathbf{x} \in \mathbb{R}^n$  from measurements  $\mathbf{y} \in \mathbb{R}^m$ :

$$\mathbf{y} = \mathbf{U}\mathbf{x}, \quad (1)$$

where  $\mathbf{U} \in \mathbb{R}^{m \times n}$  is the sensing matrix and  $\mathbf{u}_i^T$  is the  $i$ -th row. Pure random sensing matrices usually have high requirements for storage and computation. To reduce the computational cost and to simplify the hardware implementation, many structured sensing matrices have been proposed recently. [8] introduced and compared existing structured sensing matrices.

In general case, it is not possible to find  $\mathbf{x}$  when  $m < n$ , i.e., when (1) is an under-determined system. When  $\mathbf{x}$  is sparse, namely, there is only a small part of the components being non-zero, it is still possible to perfectly recover the signal. The direct measurement of sparsity is the  $\ell_0$ -norm which counts the number of non-zero components. Then the sparse recovery problem becomes

$$\min_{\mathbf{x}} \|\mathbf{x}\|_0, \quad \text{s.t.} \quad \mathbf{y} = \mathbf{U}\mathbf{x}. \quad (2)$$

Obviously, this problem is NP hard and is impossible to use in practice. In 2008, the pioneering work on compressive sensing [9] proves that when the signal is highly sparse and the sensing matrix satisfies the so-called R.I.P. condition, the signal can be recovered by a convex optimization problem:

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1, \quad \text{s.t.} \quad \mathbf{y} = \mathbf{U}\mathbf{x}.$$

Its modification for noise-corrupted data is

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 + \frac{\lambda}{2} \|\mathbf{y} - \mathbf{U}\mathbf{x}\|_{\ell_2}^2,$$

where  $\lambda > 0$  is a coefficient for the trade-off between sparsity and recovery accuracy. CS has been deeply studied: some relevant theories and mature algorithms have been reviewed in [10], [11]. The applications of CS involve various fields, such as [12], [13], [14], [15].

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### B. One-bit Compressive Sensing

In practice, CS measurements must be quantized, i.e., each measurement is mapped from a real value (over a potentially infinite range) to a discrete value over some finite range [16]. After quantification, the data can be stored and transmitted. But quantization introduces errors. An extreme case is that only one-digit quantization is used, then not like (1), the observed measurements become the sign. In other words,

$$\mathbf{y} = \text{sign}(\mathbf{U}\mathbf{x}). \quad (3)$$

This quantization method greatly reduces the number of bits in the process of transmission and storage. It can be achieved through inexpensive and fast hardware device, and it is not affected by the dynamic range problem [4]. Although the acceleration of quantization is accompanied by the loss of precision and information, this loss can be compensated by increasing the number of measurements.

To recover the signal from 1bit-CS, in [4], Boufounos and Baraniuk proposed 1bit-CS, of which the basic model is

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \mathbf{y} \odot (\mathbf{U}\mathbf{x}) \geq \mathbf{0}, \quad \|\mathbf{x}\|_2 = 1, \quad (4)$$

where  $\odot$  stands for the dot production. Comparing (2) and (4), one can find the major modifications from CS to 1bit-CS are:

- the equation requirement  $\mathbf{y} = \mathbf{U}\mathbf{x}$  is changed to the sign consistency  $\mathbf{y} \odot (\mathbf{U}\mathbf{x}) \geq \mathbf{0}$
- the norm constraint  $\|\mathbf{x}\|_2 = 1$  is additionally needed. This is because one-bit measurements have no capability to distinguish amplitude: a vector  $\mathbf{x}$  and  $a\mathbf{x}$  with any  $a > 0$  have the same one-bit measurements, i.e.,  $\text{sign}(\mathbf{u}_i^T \mathbf{x}) = \text{sign}(\mathbf{u}_i^T (a\mathbf{x}))$ ,  $\forall a > 0$ . Without loss of generality, we assume that the signal lies on the unit  $\ell_2$ -sphere. The discussion on norm estimation can be seen in [17].

The original model of 1bit-CS (4) can only deal with noise-free problems. When the sensing procedure is corrupted by noise, the sign consistency cannot be satisfied and a soft loss function was used in [16] instead of the hard constraint, resulting the following robust model for the case that the sparsity is known:

$$\min_{\mathbf{x}} \sum_{i=1}^m \max\{0, -y_i(\mathbf{u}_i^T \mathbf{x})\} \quad (5)$$

$$\text{s.t.} \quad \|\mathbf{x}\|_2 = 1, \quad \|\mathbf{x}\|_0 = K,$$

where the one-sided  $\ell_1$  loss is used. Similarly, it is also possible to use the one-sided  $\ell_2$  loss

$$\min_{\mathbf{x}} \sum_{i=1}^m (\max\{0, -y_i(\mathbf{u}_i^T \mathbf{x})\})^2$$

$$\text{s.t.} \quad \|\mathbf{x}\|_2 = 1, \quad \|\mathbf{x}\|_0 = K.$$

These two models are still non-convex but an efficient heuristic was designed by Jacques et al. in [16]. The algorithm was named as Binary Iterative Hard Thresholding (BIHT), showing that it is a modification from the well-known Iterative Hard Thresholds [18] for regular CS problems. The major modification is the calculation of the gradient term. Although the convergence of BIHT has not been theoretically proved, it showed good recovery performance, compared with matching

sign pursuit [19] and restricted-step shrinkage [6]. The use of soft loss in (5) is to deal with noise. For outliers that may induce sign flips, robust algorithms such as [20] are needed.

## III. EFFICIENT 1BIT-CS ALGORITHMS AND EXTENSION

### A. Convex 1bit-CS Models

The original 1bit-CS models are non-convex. The major difficulty is the norm constraint  $\|\mathbf{x}\|_{\ell_2} = 1$ . To pursue a convex model for 1bit-CS in order to efficiently recover sparse signal from one-bit measurements, there were many attempts. The first convex model for 1bit-CS is proposed by Plan and Vershynin in [21] using the  $\ell_1$ -norm to replace the  $\ell_2$ -norm, resulting the following problem:

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1$$

$$\text{s.t.} \quad y_i(\mathbf{u}_i^T \mathbf{x}) \geq 0, \forall i = 1, 2, \dots, m, \quad (6)$$

$$\|\mathbf{U}\mathbf{x}\|_1 = r,$$

where  $r$  is a given positive constant. The main merit is that when the first constraint is satisfied,  $\|\mathbf{U}^T \mathbf{x}\|_1$  becomes a linear function and thus (6) is convex (in fact, it is a linear programming).

Another way from (5) to convex models is to use  $\|\mathbf{x}\|_{\ell_2} \leq 1$  to approach the unit ball requirement. The corresponding model is given by [22] and takes the following formulation:

$$\min_{\mathbf{x}} -\frac{1}{m} \sum_{i=1}^m y_i(\mathbf{u}_i^T \mathbf{x})$$

$$\text{s.t.} \quad \|\mathbf{x}\|_2 \leq 1, \|\mathbf{x}\|_1 \leq s. \quad (7)$$

Here a linear function is used as the loss for sign consistency, which is essentially different to the previous models. The main advantage is the computational efficiency due to the existence of analytical solution. Besides, [23] proved that approximately sparse signals may be recovered when  $\mathbf{u}$  is sub-Gaussian. Based on (7), the constraint  $\|\mathbf{x}\|_1 \leq s$  is moved to the objective function in [24], which also discussed the sample complexity. The model becomes

$$\min_{\mathbf{x}} \gamma \|\mathbf{x}\|_1 - \frac{1}{m} \sum_{i=1}^m y_i(\mathbf{u}_i^T \mathbf{x}), \quad \text{s.t.} \quad \|\mathbf{x}\|_2 \leq 1, \quad (8)$$

where  $\gamma$  is the regularization parameter for the  $\ell_1$  norm. The corresponding optimum can be analytically solved as well and thus it is called the passive algorithm.

Besides the  $\ell_1$ -norm, other sparse penalties can be used for 1bit-CS as well. For example, [25] investigated 1bit-CS problems for sparse signals using the  $k$ -support norm and linear loss, as shown below,

$$\min_{\mathbf{x}} -\frac{1}{m} \sum_{i=1}^m y_i(\mathbf{u}_i^T \mathbf{x}), \quad \text{s.t.} \quad \|\mathbf{x}\|_k^{\text{sp}} \leq r, \|\mathbf{x}\|_2 \leq 1,$$

where  $\|\mathbf{x}\|_k^{\text{sp}}$  is the unit ball of  $k$ -support norm. Similarly to (7) and (8), the above problem has a closed-form solution as well and the solving effectiveness has been numerically shown for both Gaussian and sub-Gaussian measurements.

### B. Non-convex model for sparsity enhancement

In regular CS, the sparsity can be significantly enhanced by non-convex penalties; see, e.g., [26], [27]. For 1bit-CS, [28] found that if the linear loss is used, one can use some specific penalties, denoted by  $g(\mathbf{x})$ , to model the following problem:

$$\min_{\|\mathbf{x}\|_2 \leq 1} \mu g(\mathbf{x}) - \frac{1}{m} \sum_{i=1}^m y_i (\langle \mathbf{u}_i, \mathbf{x} \rangle) + \frac{\tau}{2} \|\mathbf{x}\|_2^2, \quad (9)$$

for which the solution can be analytically obtained as well. In [28], the smoothly clipped absolute deviation (SCAD, [29]) and minimax concave penalty (MCP, [30]) are discussed. The conclusion is extended to other positive homogeneous penalties in [31], which also showed that  $\frac{\tau}{2} \|\mathbf{x}\|$  in (9) could be removed. In this literature, the solving algorithm has been significantly improved and it is reported to be more than 200 times faster than (9) in numerical experiments.

In TABLE I, the mentioned algorithms are listed.

### C. Mixed 1bit-CS

For relatively small number of measurements, CS is efficient to recover sparse signals. If the measurements all contain only one-bit, 1bit-CS is suitable and there have been many algorithms for them, as reviewed previously. It is also possible that we meet analog measurements and one-bit measurements simultaneously. A typical scene is that when the detectable range is limited in a sensing system, then (1) becomes

$$\mathbf{y} = \max\{s_-, \min\{\mathbf{U}\mathbf{x}, s_+\}\}, \quad (10)$$

where  $s_+$  and  $s_-$  are the upper and lower threshold, respectively. That means we can only observe the value when  $\mathbf{U}\mathbf{x}$  is in the detectable  $[s_-, s_+]$ , otherwise, the observation is  $s_+$  or  $s_-$ . When saturation phenomenon happens, traditional methods are to detect the saturated samples and drop them away.

In the view of 1bit-CS, saturated measurements contain one-bit information:  $\mathbf{U}\mathbf{x} \geq s_+$  if  $y_i = s_+$  and  $\mathbf{U}\mathbf{x} \leq s_-$  if  $y_i = s_-$ . Unlike the pure 1bit-CS, besides one-bit measurements, (10) has analog measurements as well. Thus, CS and 1bit-CS are simultaneously considered, resulting in the so called mixed one-bit compressive sensing (M1bit-CS), which could be modeled as

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mu \|\mathbf{x}\|_1 + \sum_{\Psi_i=0} L_1(\mathbf{u}_i^T \mathbf{x} - y_i) + \lambda \sum_{\Psi_i=1} L_2(z_i(\mathbf{u}_i^T \mathbf{x} - s_i)) \\ \text{s.t.} \quad & \|\mathbf{x}\|_2 \leq 1, \end{aligned} \quad (11)$$

where  $\Psi$  is an indicator vector for saturation,  $z_i \in \{-1, +1\}$  is used to distinguish the upper-saturation ( $z_i = 1$ ) and lower-saturation ( $z_i = -1$ ). Here, two loss functions are used:  $L_1$  is for analog measurements and  $L_2$  is for one-bit measurements. Compared to 1bit-CS, there are additionally analog measurements, which makes the norm constraint less important. Anyway, in M1bit-CS, the prior-knowledge about the norm helps the signal recovery, while the effect is weakened with more analog measurements.

There are multiple choices for the loss functions (or indicator function). For noise-free cases, the model and statistical analysis can be found in [32]. If the analog measurements

are corrupted by noise but the one-bit measurements have no flips, the readers are referred to [33]. When noise on the two parts cannot be avoided,  $L_1(u) = u^2$  and  $L_2(u) = \max\{0, u\}$  are used in [34], where (11) is solved by alternating direction method of multipliers (ADMM) as summarized in Alg. 1.

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#### Algorithm 1 ADMM for M1bit-CS

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**Initialize:**

$$\mathbf{x}, \mathbf{z}, \boldsymbol{\beta} := \mathbf{0}_d, \mathbf{e}, \boldsymbol{\alpha} := \mathbf{0}_m, \theta_1, \theta_2 > 0$$

**repeat**

$e_i := \mathbb{S}(z_i(s_i - \mathbf{u}_i^T \mathbf{x}) - \frac{\alpha_i}{\theta_1}, \mu/\theta_1), \forall \Psi_i = 1$ , where  $\mathbb{S}$  is the soft thresholding operator

$\mathbf{z} := \mathcal{P}(\mathbf{x} - \boldsymbol{\beta}/\theta_2)$ , where  $\mathcal{P}_c$  is the projection operator to the ball  $\|\mathbf{x}\|_2 \leq 1$

update  $\mathbf{x}$  by solving a quadratic programming plus a sparse penalty, which has analytical solution

$$\boldsymbol{\alpha} := \boldsymbol{\alpha} + \theta_1(\mathbf{e} - \mathbf{s} + \mathbf{U}\mathbf{x})$$

$$\boldsymbol{\beta} := \boldsymbol{\beta} + \theta_2(\mathbf{z} - \mathbf{x})$$

**until** stopping criteria is satisfied.

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## IV. APPLICATIONS OF 1BIT-CS

Because of the high efficiency of one-bit sampling, 1bit-CS has been applied to many fields. In some situations, one-bit sampling is not on purpose but is induced by saturation, for which the mentioned methods are applicable to fully utilize one-bit information.

In wireless sensor networks (WSNs), the sensor readings are compressible. In addition, bandwidth and energy are constrained for sensors in WSNs. For these reasons, 1bit-CS is suitable to compress sensor readings. In [35], 1bit-CS was applied for data gathering in WSNs, and a blind reconstruction algorithm was designed. Experiments in [35] showed improvement on compression ratio, which reduced communication cost. In [36], 1bit-CS was applied to source localization in WSNs. A method using Gaussian entropy for sparse signal recovery was designed in [36] and improved the accuracy for localizing the targets. In [37], 1bit-CS over noisy WSNs subject to channel-induced bit flipping errors was considered, and an amplitude-aided signal reconstruction scheme was proposed. This scheme improves the accuracy when the SNR is low or the number of sensors is small.

Another application of 1bit-CS is data processing for radar. In radar systems, the received signals are encoded on board and then downlinked to the ground station. It is important to ease the burden of data transmission, and 1bit-CS is a proper choice. A 1bit-CS approach for synthetic aperture radar (SAR) imaging of sparse scenes was designed in [38], where the ghost target was eliminated and the noisy background was suppressed. A compressive pulse-Doppler radar that works through one-bit quantization of the received noisy signal was designed in [39], which also discussed the corresponding sparse recovery method and this method had promising performance in the detection/estimation of the target parameters. Discussions were provided in [40] and [41] to describe the performance of one-bit coded radar signals, the effect of noise, and the fast convolution methods in time domain, which was useful for improving the performance of radar.

TABLE I: Summary of 1bit-CS Algorithms

models	convexity	characteristic	algorithm
L. Jacques, et al. 2013	nonconvex	$\ell_0$ constraint for sparsity, one-sided $\ell_1/\ell_2$ loss for noise, and $\ell_2$ -norm sphere for signal's norm	heuristic (BIHT)
Y. Plan and R.Vershynin 2013	convex	$\ell_1$ norm for sparsity, constraints for sign consistency, and $\ell_1$ -norm sphere for signal's norm	linear programming
Y. Plan and R.Vershynin 2013	convex	linear loss for sign consistency, $\ell_1$ -norm constraint for sparsity, and $\ell_2$ -norm ball for signal's norm	quadratic constrained programming
L. Zhang, et al. 2014	convex	$\ell_1$ norm for sparsity, linear loss for sign consistency, and $\ell_2$ -norm ball for signal's norm	passive algorithm (analytical solution)
S. Chen, et al. 2015	convex	linear loss for sign consistency, k-support norm constraint for sparsity, and $\ell_2$ -norm ball for signal's norm	k-support norm estimator
R. Zhu, et al. 2015	nonconvex	SCAD/MCP for sparsity, linear loss for sign consistency, and $\ell_2$ -norm ball for signal's norm	analytical solution
X. Huang and M. Yan 2018	nonconvex	positive homogeneous penalties for sparsity, linear loss for sign consistency, and $\ell_2$ -norm ball for signal's norm	analytical solution

It is also promising to use one-bit information in biomedical field, since many biological signals are sparse or sparse in particular wavelets, such as electrocardiogram, electromyogram, electroencephalogram, CT, and magnetic resonance imaging. Javier Haboba et al. presented a new architecture of analog to digital converter that produces 1-bit compressive measurements [42]. The effectiveness of the architecture and of its enhancement is also shown in [42] with applications to electroencephalo-graph. This makes 1bit-CS more practical.

## V. M1BIT-CS ON CT RECONSTRUCTION

Here, we illustrate an application of M1bit-CS on CT reconstruction from overexposed measurements. When the projection is perfectly detected, then classical algorithms, such as filtered back projection (FBP, [43]), can easily output high-qualified images. In Figure 1(a), the projections of a phantom reported in [44] is shown. When overexposure happens, part of the projections cannot be detected, as displayed in Figure 1(b), from which simply utilizing the FBP leads to bad reconstruction performance; see Figure 2(b).

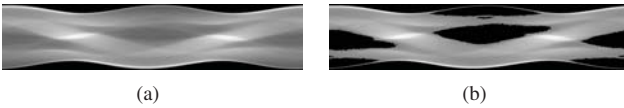


Fig. 1: (a) Full projection; (b) Projection with saturation.

As discussed previously, those overexposed projections still provide one-bit information, which enables the use of M1bit-CS. In Figure 2(d), the corresponding reconstruction result is compared with both FBP and total variation based simultaneous algebraic reconstruction technique (SART-TV, [45], [46]), showing M1bit-CS could significantly reduce both the typical streaking artifacts and capping artifacts, and improve the image reconstruction quality. This improvement comes from the use of one-bit information, from which it follows a broad foreground for handling systems with saturation.

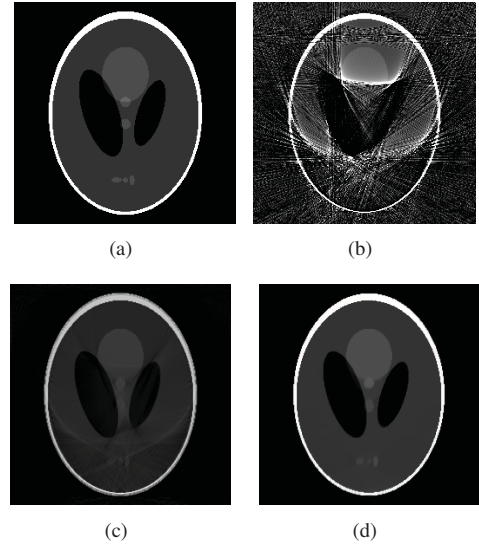


Fig. 2: (a) Reconstruction image from projections Fig.1(a); (b) Reconstruction image by FBP for saturated projections Fig.1(b); (c) Reconstruction image by SART-TV for saturated projections Fig.1(b); (d) Reconstruction image by M1bit-CS for saturated projections Fig.1(b)..

## VI. CONCLUSION AND FUTURE PROSPECTS

For sparse signal recovery from one-bit measurements, 1bit-CS has attracted research attention in the last decade. The models and algorithms are reviewed in this paper, together with the introduction of M1bit-CS and applications on wireless sensor networks, radar, and CT reconstruction. The main advantage of 1bit-CS is the sampling efficiency, which is closely related to hardware design. With specifically designed sampling hardware, it is promising to use 1bit-CS in many applications. In the future, new reconstruction algorithms with low complexity and high precision are still needed, and the applications of 1bit-CS in various fields are also waiting for further exploration. In addition, there is also lots of work to be done to implement the one-bit quantitative sampling circuit.



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