Denoising and Error Correction in Wireless Sensor Networks

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Abstract – *Measurements of wireless sensor networks (WSNs) are often polluted by random measurement noises and corrupted by unpredictable sensory reading errors. For a typical field monitoring scenario, this paper considers to correct sensory reading errors and recover the monitoring field, subject to measurement noises. The key factor to enable successful denoising and error correction is that the monitoring field can often be represented by a sparse signal vector; signal sparsity makes sensory readings of WSNs to be redundant, which offers inherent fault tolerance against measurement noises and sensory reading errors.*

Specifically, this paper focuses on two approaches: one is the ℓ_1 regularized least squares (LRLS) approach which was proposed to handle noises in statistical signal processing, and the other is the cross-and-bouquet (CAB) approach which was proposed to correct errors in computer vision. Discussion of their relationship reveals that the CAB approach is robust to measurement noises, while the two approaches have similar performance when sensory reading errors are dense. Extensive simulation results validate the effectiveness of the two approaches.

Keywords: Wireless sensor networks (WSNs), field monitoring, denoising and error correction.

1 Introduction

In recent years, wireless sensor networks (WSNs) have attracted much attention in applications of field monitoring [1]. A large amount of low-cost wireless sensor nodes, which are capable of sensing and communicating even under extreme conditions, are deployed in a monitoring field, forming a large-scale WSN. Typical application scenarios include acoustic source localization [2], mine accident prediction [3], structural health monitoring [4, 5], etc.

However, the sensory readings of WSNs, being collected by a fusion center, are unavoidably subject to measurement noises and sensory reading errors in such applications. Here we emphasize the difference between measurement noises and sensory reading errors as:

1) *Measurement noises* exist for all sensor nodes, which limit the performance of any measurement systems. Measurement noises generally can be treated as low-level, independent and identically distributed disturbance for all sensor nodes.

2) *Sensory reading errors* affect only a section of the sensor nodes but the error level may be high; the errors, on the other hand, are possibly dependent. For example, the reading of one sensor node may be severely corrupted during wireless multi-hop communications and turning to be extremely large; or it may be lost, resulting in a report of zero at the fusion center. Furthermore, damage of one critical relaying sensor node will lead to not only a report of zero for itself, but also reports of zeros for a bunch of relayed sensor nodes.

To summarize, a general measurement model for the field monitoring applications can be written as:

$$\mathbf{b} = \mathbf{F}\mathbf{x} + \mathbf{n} + \mathbf{e} \tag{1}$$

in which $\mathbf{b}$ is the vector of sensory readings collected by the fusion center; $\mathbf{F}$ is the measurement matrix; $\mathbf{x}$ is the signal vector representing the monitoring field; $\mathbf{n}$ is the vector of measurement noises; $\mathbf{e}$ is the vector of sensory reading errors. Contrary to the dense noise vector $\mathbf{n}$, the error vector $\mathbf{e}$ is generally sparse, namely, containing many zeros.

In this paper we will try to answer the following question: *given sensory readings and measurement matrix, how can we design efficient signal recovery algorithms, which are robust to random measurement noises and unpredictable sensory reading errors?* Our contributions are two-fold:

1) We formulate the field monitoring problem as recovering a sparse signal which represents the monitoring field. The monitoring field contains multiple

point sources of interest, which is effectively represented by a simple sparse linear regression model. Exploiting signal sparsity enables efficient denoising and error correction.

2) We investigate the inherent denoising versus error correction capability of sparse signal recovery through two approaches: one is the ℓ_1 regularized least squares (LRLS) approach which was originally proposed to handle noises in statistical signal processing [6, 7], and the other is the cross-and-bouquet (CAB) approach which was originally proposed to correct errors in computer vision [8, 9, 10]. We analyze the relationship between the two approaches and show that they both regularize the signal to be recovered via exploiting signal sparsity. The analysis reveals that the CAB approach is robust to measurement noises, while the two approaches have similar performance when sensory reading errors turn to be dense.

The remainder of this paper is organized as follows. The denoising and error correction approaches are considered in Section 2. The relationship between the LRLS and CAB approaches is analyzed theoretically. Section 3 establishes the basic models for the field monitoring task of WSNs. Section 4 provide extensive simulation results to evaluate the effectiveness of proposed methods. Section 5 concludes the paper and discusses several future directions.

2 Denoising & Error Correction

In this section, we first discuss several existing denoising and error correction methods. Then we focus on two approaches, LRLS and CAB, and analyze their relationship.

2.1 Related Work

If no prior knowledge is available for the measurement system in equation (1), the natural way to recover the signal vector $\mathbf{x}$ is to use a least squares (LS) estimator:

$$\hat{\mathbf{x}}_{LS} = \arg\min ||\mathbf{b} - \mathbf{F}\mathbf{x}||_2^2 \tag{2}$$

The LS estimator is the best linear unbiased estimator (BLUE) when $\mathbf{n}$ is a white noise vector and $\mathbf{e}$ is zero. Generally, the LS estimator neither provides a sparse solution nor corrects errors. Prior knowledge needs to be utilized in order to improve the quality of signal recovery.

For denoising in the absence of the error vector $\mathbf{e}$, a useful prior knowledge is that the signal vector $\mathbf{x}$ is sparse. The signal sparsity is hence appended as a regularization term to the LS estimator, leading to the ℓ_1 regularized least squares formulation (LRLS) [6, 7]:

$$\hat{\mathbf{x}}_{LRLS} = \arg\min ||\mathbf{x}||_1 + \frac{\lambda_{LRLS}}{2}||\mathbf{b} - \mathbf{F}\mathbf{x}||_2^2 \tag{3}$$

in which λ_{LRLS} is a positive weight to balance the ℓ_2 norm of residuals and the sparsity of $\mathbf{x}$. The ℓ_1 norm of $\mathbf{x}$, representing the signal sparsity, is the relaxation of the ℓ_0 norm of $\mathbf{x}$ and makes the recovery problem tractable.

Equation (3) has two closely related formulations. The first one is the basis pursuit denoising (BPDN) [11], being a quadratically constrained linear program:

$$\hat{\mathbf{x}}_{BPDN} = \arg\min_{||\mathbf{b}-\mathbf{F}\mathbf{x}||_2^2 \le \epsilon} ||\mathbf{x}||_1 \tag{4}$$

The second one is the least absolute shrinkage and selection operator (LASSO) [12] which appears in feature selection, as a linearly constrained quadratic program:

$$\hat{\mathbf{x}}_{LASSO} = \arg\min_{||\mathbf{x}||_1 \le \tau} ||\mathbf{b} - \mathbf{F}\mathbf{x}||_2^2 \tag{5}$$

Convex analysis [6] shows that a solution to equation (4), for any ϵ such that this problem is feasible, is either $\mathbf{c} = \mathbf{0}$ or a minimizer of equation (3) for some $\lambda_{LRLS} \ge 0$. Similarly, a solution of equation (5), for any $\tau \ge 0$, is also a minimizer of equation (3) for some $\lambda_{LRLS} \ge 0$. Therefore in this paper we use LRLS to stand for this set of denoising methods. However, the possibility of error correction when the error vector $\mathbf{e}$ being nonzero has not been discussed for these approaches.

Another parallel line is error correction. For computer vision problems, [8, 9, 10] prove that the error vector $\mathbf{e}$ can be corrected given that the noise vector $\mathbf{n}$ is zero and the signal vector $\mathbf{x}$ is sparse. This cross-and-bouquet (CAB) approach simultaneously recovers both $\mathbf{x}$ and $\mathbf{e}$ via a linear program:

$$[\hat{\mathbf{x}}_{CAB}; \hat{\mathbf{e}}_{CAB}] = \arg\min_{\mathbf{b}=\mathbf{F}\mathbf{x}+\mathbf{e}} ||[\mathbf{x}; \mathbf{e}]||_1 \tag{6}$$

It is illustrated in [8, 9, 10] that the CAB approach is able to correct an image even with more than 60% pixels being arbitrarily corrupted. But its performance in the presence of measurement noises is still an open question.

All the above-mentioned approaches can be discussed in the context of compressive sensing [13, 14]. The theories of compressive sensing demonstrated the impact of sparsity on signal processing. Another notable error correction approach, which directly adopts the idea of compressive sensing but considers the sparsity of the error vector, is proposed in [15]. When $\mathbf{n}$ is zero, $\mathbf{e}$ is sparse, and $\mathbf{G}$ spans the null space of $\mathbf{F}$ such that $\mathbf{G}\mathbf{F} = 0$, then equation (1) turns to be $\mathbf{G}\mathbf{b} = \mathbf{G}\mathbf{e}$. Hence the sparse error vector $\mathbf{e}$ can be recovered from the linear program (LP):

$$\hat{\mathbf{e}}_{LP} = \arg\min_{\mathbf{G}\mathbf{b}=\mathbf{G}\mathbf{e}} ||\mathbf{e}||_1 \tag{7}$$

with high probability given that $\mathbf{G}$ satisfies certain properties. Minimization of $||\mathbf{e}||_1$ leads to a sparse solution subject to the constraint $\mathbf{G}\mathbf{b} = \mathbf{G}\mathbf{e}$. Then the signal vector $\mathbf{x}$ can be further recovered. However, this approach is confined to the case that the noise vector is 0 and $\mathbf{GF} = 0$ holds for some nonzero $\mathbf{G}$. When the measurements are polluted by noises or the measurement matrix $\mathbf{F}$ is fat, the LP approach may fail.

2.2 Relationship between LRLS & CAB

This paper tries to bridge the gap between denoising and error correction, which has not been addressed before. We focus on the LRLS and CAB approaches and discuss their relationship. Specifically, we show that the CAB approach is capable of denoising, while the LRLS approach will perform similarly with the CAB approach when the errors turn to be dense.

At the first glance the CAB formulation in equation (6) appears to be questionable since we are treating the signal and noise vectors equivalently via looking for a sparse solution of the catenated vector $[\mathbf{x}; \mathbf{e}]$. However, noticing $||[\mathbf{x}; \mathbf{e}]||_1 = ||\mathbf{x}||_1 + ||\mathbf{e}||_1$ and substituting the linear constraint $\mathbf{b} = \mathbf{Fx} + \mathbf{e}$ to the objective function of equation (6), we have:

$$[\hat{\mathbf{x}}_{CAB}; \hat{\mathbf{e}}_{CAB}] = \arg \min_{\mathbf{b}=\mathbf{Fx}+\mathbf{e}} ||\mathbf{x}||_1 + ||\mathbf{b} - \mathbf{Fx}||_1 \quad (8)$$

The objective function in equation (8) does not contain $\mathbf{e}$, thus we can treat $\mathbf{e}$ as a slack vector. The constraint $\mathbf{b} = \mathbf{Fx}+\mathbf{e}$ can be hence eliminated since we can always find some $\mathbf{e}$ to satisfy this constraint for any $\mathbf{x}$:

$$\hat{\mathbf{x}}_{CAB} = \arg \min ||\mathbf{x}||_1 + ||\mathbf{b} - \mathbf{Fx}||_1 \quad (9)$$

Equation (9) is the special case of the following formulation, when the positive weight $\lambda_{CAB} = 1$:

$$\hat{\mathbf{x}}_{CAB} = \arg \min ||\mathbf{x}||_1 + \lambda_{CAB}||\mathbf{b} - \mathbf{Fx}||_1 \quad (10)$$

Comparing equation (3) and equation (10), we can clearly observe the relationship between LRLS and CAB:

1) The two approaches both recover the sparse signal vector $\mathbf{x}$ via minimizing its ℓ_1 norm $||\mathbf{x}||_1$.

2) The two approaches adopts different strategies to handle residuals. The LRLS approach minimizes the ℓ_2 norm of the residuals, while the CAB approaches minimizes the ℓ_1 norm of the residuals.

The relationship between LRLS and CAB is an analogy of the relationship between the LS estimator and the following least absolute deviations (LAD) estimator [19, 20]:

$$\hat{\mathbf{x}}_{LAD} = \arg \min ||\mathbf{b} - \mathbf{Fx}||_1 \quad (11)$$

Comparing to LS, LAD is resistant to large but sparse outliers. From the perspective of compressive sensing, LAD makes the residuals sparse. The advantage of CAB over LAD, similar to that of LRLS over LS, is the use of signal sparsity which enhances recovery performance. Since LAD is robust to noises in recovering non-sparse signals, we conclude that CAB is also capable of denoising in recovering sparse signals. The low-level noises, though biasing the estimation, have limited influence on the accuracy of recovery. This conclusion coincides with the empirical observation in [9]; namely, CAB is robust in the presence of noises.

However, when the sensory reading errors are dense, the CAB approach will have similar performance to that of the LRLS approach. The reason is, when the residuals are no longer sparse, their ℓ_1 norm $||\mathbf{b} - \mathbf{Fx}||_1$ and ℓ_2 norm $||\mathbf{b} - \mathbf{Fx}||_2$ have no essential difference. This is contrary to the case that the minimization of $||\mathbf{x}||_1$ and the minimization of $||\mathbf{x}||_2$ are totally different if we want to recover a sparse signal vector $\mathbf{x}$. Therefore, the LRLS approach will have similar performance to the CAB approach when the errors are dense.

It is suggested in [9] that appending a weighted ℓ_2 term of residuals to the objective function of equation (6) can improve the robustness of the CAB approach in the presence of noises. This leads to the CAB-LRLS formulation:

$$\hat{\mathbf{x}}_{CAB-LRLS} = \arg \min \\ ||\mathbf{x}||_1 + \lambda_{CAB}||\mathbf{b} - \mathbf{Fx}||_1 + \tfrac{\lambda_{LRLS}}{2}||\mathbf{b} - \mathbf{Fx}||_2^2 \quad (12)$$

This idea is similar to the one which appears in the recent paper [20], with the name of LS-LASSO:

$$[\hat{\mathbf{x}}_{LS-LASSO}; \hat{\mathbf{e}}_{LS-LASSO}] = \arg \min \\ ||\mathbf{x}||_1 + \lambda_{LASSO}||\mathbf{e}||_1 + \tfrac{\lambda_{LS}}{2}||\mathbf{b} - \mathbf{Fx} - \mathbf{e}||_2^2 \quad (13)$$

CAB-LRLS balances denoising and error correction via regularizing the residuals with both ℓ_1 and ℓ_2 norms. LS-LASSO explicitly treats noises and errors in different ways; the noises are suppressed with their ℓ_2 norm and the sparse errors are recovered with their ℓ_1 norm. The main difficulty in implementing CAB-LRLS and LS-LASSO is how to choose proper weights.

In addition, we can also consider what will happen if we impose a constraint on the ℓ_∞ norm of the residuals or their linear projections. The Dantzig selector (DS):

$$\hat{\mathbf{x}}_{DS} = \arg \min_{||\mathbf{F}^T(\mathbf{b}-\mathbf{Fx})||_\infty \leq \delta} ||\mathbf{x}||_1 \quad (14)$$

or its variant:

$$\hat{\mathbf{x}}_{DS} = \arg \min ||\mathbf{x}||_1 + \lambda_{DS}||\mathbf{F}^T(\mathbf{b} - \mathbf{Fx})||_\infty \quad (15)$$

has been proposed in [21] for denoising. Minimization of the ℓ_∞ norm $||\mathbf{F}^T(\mathbf{b} - \mathbf{Fx})||_\infty$, namely the largest absolute value of the projected residuals, implies the suppression of residuals. The analysis above also suggests that DS is similar to LRLS and CAB in denoising and correcting dense errors.

In this paper, we focus on the LRLS and CAB approaches in a field monitoring scenario, and demonstrate their capability of denoising and error correction via exploiting signal sparsity.

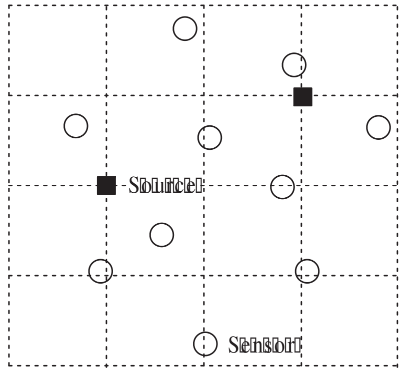

Figure 1: The monitoring field is viewed as a spatial grid. The sources of interest, denoted by solid squares, are confined to occur at the grid points. The sensor nodes, denoted by hollow circles, measure the influences of the sources and then report to a fusion center.

3 Problem Formulation

Consider a large-scale WSN which is randomly deployed in a two-dimensional area. The network has a set of L sensor nodes, denoted as $\mathcal{L} = \{v_l\}_{l=1}^{L}$. Suppose that at one snapshot, multiple sources may occur in the monitoring field. The sensor nodes measure the influences of the sources and then report to a fusion center. The fusion center processes the collected sensory readings and estimate the positions and strengths of the sources. We make the following basic assumptions for the sensing problem of interest:

(A1): The monitoring field is viewed through a spatial grid with K grid points denoted by $\mathcal{K} = \{g_k\}_{k=1}^{K}$. Each source can occur only at a grid point, indicating the spatial resolution offered by the network. The strength of a source occurring at grid point g_k is x_k, which can be either positive or negative.

(A2): The influence of a unit-strength source at grid point g_k on a sensor node v_l is f_{kl}. Generally speaking, the influence function f_{kl} is decided by distance d_{kl} between g_k and v_l.

(A3): The measurement of one sensor node is the linear superposition of the influences of all sources, polluted by a measurement noise. During transmission to the fusion center, the measurement is further corrupted by a sensory reading error. The reading b_l of sensor node v_l, received by the fusion center, is hence $b_l = \sum_{k=1}^{K} f_{kl}x_k + n_l + e_l$ in which n_l is the measurement noise and e_l is the sensory reading error.

Remark 1: The assumption **(A1)** simplifies the recovery problem by confining the sources to grid points. Without this assumption, an alternative idea is to use positions and strengths of the sources as decision variables and formulate a least squares problem. However, this formulation is highly nonlinear and intractable, since even the number of decision variables may be unknown. Based on the assumption **(A1)**, we can formulate the otherwise nonlinear problem as recovering the vector $\mathbf{x} = [x_1, ..., x_K]^T$ from the sensory readings $\{b_l\}_{l=1}^{L}$. Entries in $\mathbf{x}$ with nonzero values indicate the locations and strengths of the multiple sources of interest. This assumption approximately holds when the grid points are dense; namely, the density of the grid points decides the spatial resolution of the recovery algorithm, as depicted in Fig. 1.

Remark 2: The assumption **(A2)** describes the influence of one source on the entire monitoring field. For example, in acoustic source localization or nuclear radioactive detection applications [16, 17], the influence of a source decreases polynomially as the distance increases. Without loss of generality, we define the influence function as $f_{kl} = \exp(-d_{kl}^2/\sigma^2)$ for grid point g_k and sensor point v_l, where σ is a common constant. This Gaussian-shaped function well approximates the influence of many practical sources [4, 5].

Remark 3: The assumption **(A3)** models the sensory readings received by the fusion center. A sensory reading b_l is composed of three parts: information from the sources, random measurement noise, and sensory reading error. Hence the measurement model can be written as $\mathbf{b} = \mathbf{F}\mathbf{x} + \mathbf{n} + \mathbf{e}$, as in equation (1). Here $\mathbf{b} = [b_1, ..., b_L]^T$ is the sensory reading vector, $\mathbf{n} = [n_1, ..., n_L]^T$ is the noise vector, $\mathbf{e} = [e_1, ..., e_L]^T$ is the error vector, and $\mathbf{F}$ is the $L \times K$ measurement matrix with its l-th row given by $[f_{1l}, ..., f_{Kl}]$.

For practical applications in a large monitoring field, the number of sources is often much smaller than the number of grid points, given that the spatial resolution is reasonable [2, 18]. Therefore, the signal vector $\mathbf{x}$ is sparse, namely, $\mathbf{x}$ contains mainly zero elements. The signal sparsity plays a key role for successful denoising and error correction, as we will demonstrate in the numerical experiments.

4 Simulation Results

In this section we provide extensive simulation results to evaluate various denoising and error correction approaches. Specifically, we consider that 100 sensor nodes are uniformly randomly deployed in a 100×100 square monitoring area. Four uniformly randomly chosen sources, two of them having strengths 1 and two of them having strengths -1, occur in the monitoring area. The parameter σ is fixed as 40 in the influence function $f_{kl} = \exp(-d_{kl}^2/\sigma^2)$.

We first consider the case of a tall measurement matrix, namely, the number of grid points is smaller than the number of sensor nodes. Then we consider the case of a fat measurement matrix, namely, the number of grid points is larger than the number of sensor nodes.

The performance of denoising and error correction can be evaluated via two criteria: number of false alarms and number of miss detections. We define there is a false alarm if one grid point has no source but the estimator detects a signal whose strength is larger than 0.05 or smaller than -0.05. Similarly we define there is a miss detection if one grid point has a source with strength 1 but the estimator detects a signal strength smaller than 0.05 or larger than 20, or if one grid point has a source with strength -1 but the estimator detects a signal strength larger than -0.05 or smaller than -20.

Measurement noises are imposed to all sensor nodes. They are supposed to be uniformly and independently distributed from $-M_n$ to M_n, in which M_n is the noise level. For sensory reading errors, we randomly choose a section of measurements and corrupt them via setting as 0. All simulations are repeated for 100 times based on the optimization toolbox CVX [22] to calculate the average value.

4.1 Tall Measurement Matrix

The monitoring field is split to a 6×6 grid, leading to an over-determined problem. If the measurement matrix is tall, the LP approach in equation (7) is applicable. We also simulate the LS estimator in equation (2) and the LAD estimator in equation (11) as comparisons.

When the measurement noises are zero, namely $M_n = 0$, the results of different approaches are shown in Fig. 2. The CAB approach achieves the best performance if the sensory reading errors are sparse. When the ratio of errors increases, the CAB and LRLS approaches will have similar recovery performance; this verifies the our theoretical analysis. The LP and LAD estimators can correct sparse errors but incapable of correcting dense errors. It is not surprising that their results are very similar, since LP is solving the sparsest $\mathbf{e}$ from the linear system $\mathbf{Ge} = \mathbf{G}(\mathbf{Fx} - \mathbf{b})$ while LAD is solving the sparsest $\mathbf{e}$ from the linear system $\mathbf{e} = \mathbf{Fx} - \mathbf{b}$. The CAB approach is superior to LAD for dense errors due to the exploitation of signal sparsity via appending a regularized term $||\mathbf{x}||_1$.

When the noise level is $M_n = 0.05$, the simulation results are depicted in Fig. 3. The LRLS approach is robust to noises, and shows the capability of correcting errors. The CAB approach is also robust in the presence of noises, though the number of false alarms increases. The LP and LAD estimators both fails in this case, showing the importance of incorporating signal sparsity for denoising and error correction.

4.2 Fat Measurement Matrix

In the fat measurement matrix case, the monitoring field is split to an 11×11 grid, hence the problem is under-determined. In this case, the LS, LP, and LAD estimators are all unable to recover the monitoring field. Contrarily, the LRLS and CAB approaches still demonstrate stable recovery performance, as shown in Fig. 4 and Fig. 5. Via using the prior knowledge of signal sparsity, the regularized term $||\mathbf{x}||_1$ helps find the sparsest $\mathbf{x}$ from the under-determined systems.

5 Conclusions

For a typical field monitoring application of WSNs, this paper considers to recover a sparse signal from collected sensory readings, which are polluted by random measurement noises and corrupted by unpredictable sensory reading errors. With extensive simulation results, we illustrate that exploitation of signal sparsity enables successful denoising and error correction, no matter whether the measurement system is over-determined or under-determined.

The two denoising and error correction approaches, LRLS and CAB, both incorporate the prior knowledge of signal sparsity and thus improve the performance of signal recovery. The CAB approach, which further implies the sparsity of residuals, shows perfect performance when the errors are sparse; however, it is still robust to low-level noises. The LRLS approach, which tends to have non-sparse residuals, can correct dense errors to some extent. Understanding the embedded ideas of these approaches enables us to design proper denoising and error correction algorithms for specific systems.

Starting from this point, our future work includes the following directions:

1) The first topic of interest is to improve the performance of signal recovery when the sensory reading errors appear to be highly correlated [8, 9]. This phenomenon often happens in a WSN when a relaying node fails and hence a large amount of relayed measurements are lost. Prior knowledge for the correlation of errors may help for this issue.

2) The second topic is to design efficient algorithms to balance the ℓ_1 and ℓ_2 norms of the residuals. As we mentioned above, the CAB-LRLS and LS-LASSO approaches provide a systematic method to balance different norms; however, how to choose proper weights is a non-trivial task. One possible strategy is to calculate the full solution path for different weights; this strategy inevitably induces high computational complexity. Knowing that the estimates are often piecewise linear to the weights may help reduce the computational burden [20].

3) The third topic is to implement the denoising and error correction approaches in a decentralized way. Decentralized signal processing is able to improve the scalability and robustness of WSNs [23]. However, in order to guarantee stable convergence, how to handle errors in information exchange is still a significant challenge [24].

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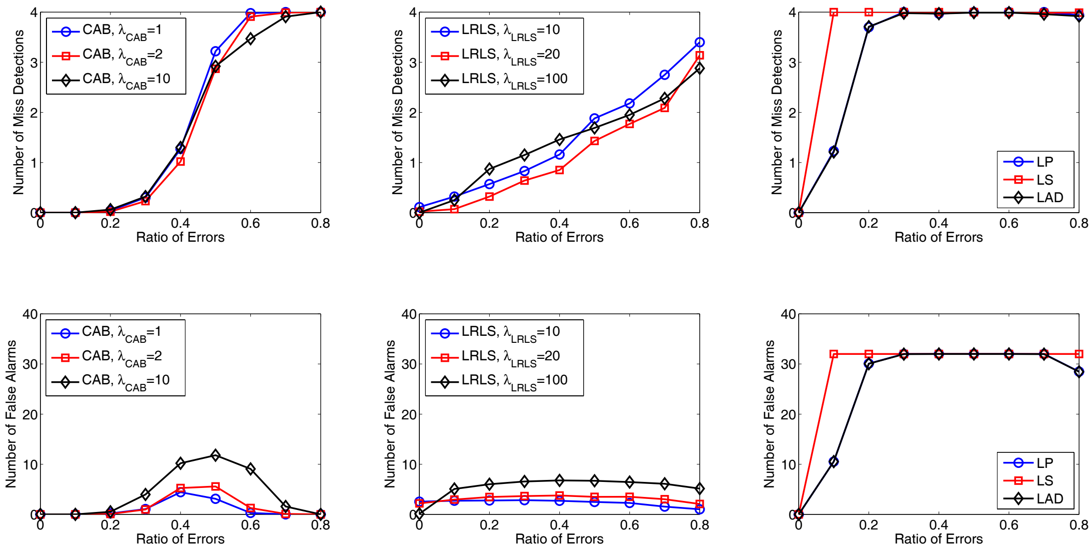

Figure 2: Number of miss detections and false alarms for different denoising and error correction approaches when the measurement matrix is tall and the sensory readings are noise-free.

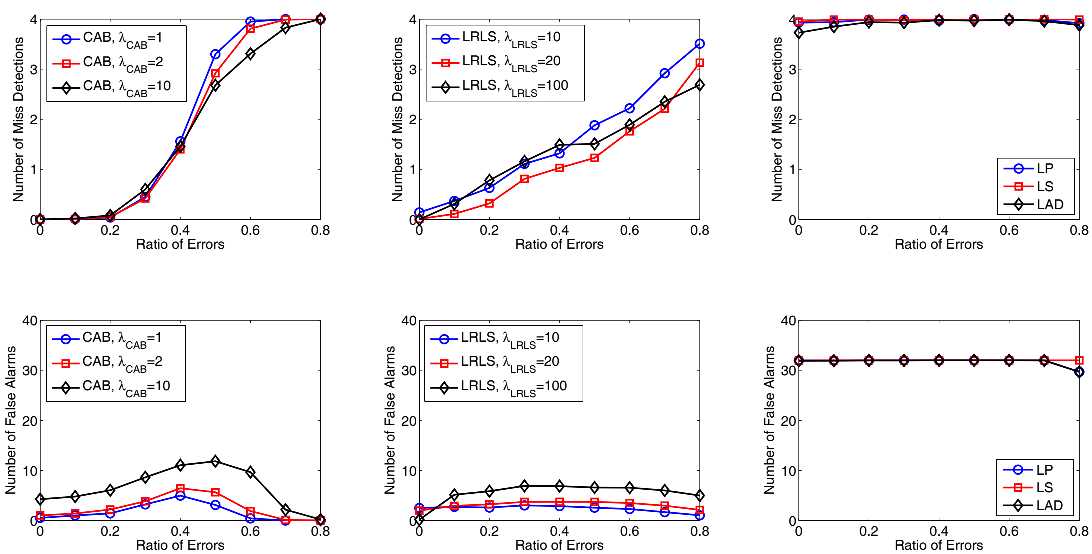

Figure 3: Number of miss detections and false alarms for different denoising and error correction approaches when the measurement matrix is tall and the sensory readings are noise-polluted.

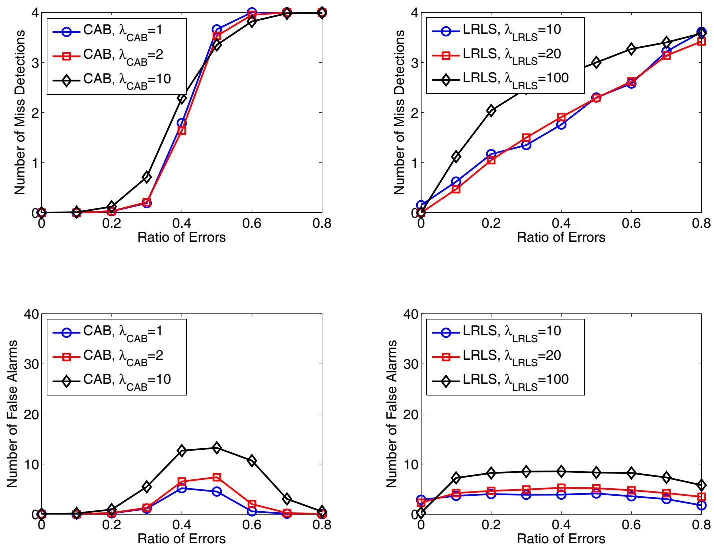

Figure 4: Number of miss detections and false alarms for different denoising and error correction approaches when the measurement matrix is fat and the sensory readings are noise-free.

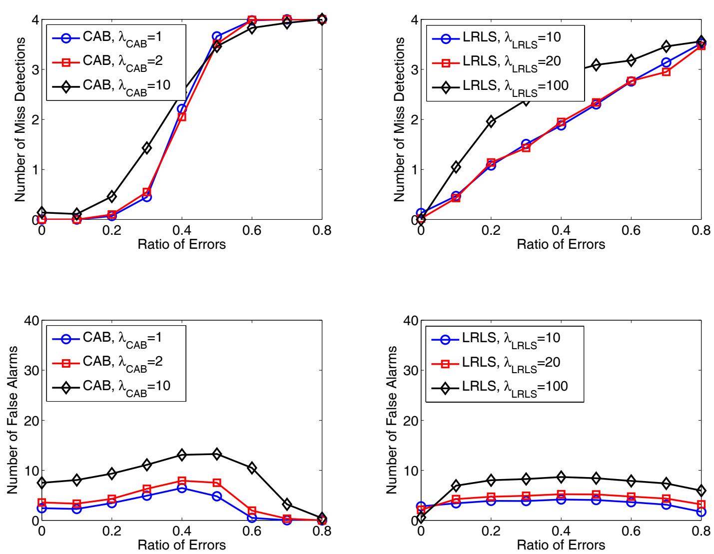

Figure 5: Number of miss detections and false alarms for different denoising and error correction approaches when the measurement matrix is fat and the sensory readings are noise-polluted.

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