Research Article

Improving Rare Events Detection in WSN through Cluster-Based Power Control Mechanism

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Rare events detection is one of the main applications in Wireless Sensor Networks (WSN) and is currently a central concern of a vast literature. Compressed Sensing (CS) theory has been proved to be quite adapted to this objective. Although this is not the first work on applying CS to sparse events detection in WSN, it is the first to highly justify the validity of the targets detection and counting problem formulation. In order to enhance the CS recovery capacity in WSN, this work considers an approach based on a coherence reduction of the sensing matrix premised on the transmitted power control (PC). Simulation results prove that, under the constraint of equal power consumption, the detection and counting performance is improved when the proposed power control scheme is employed compared to the case without PC.

1. Introduction

Wireless Sensor Networks (WSN) are widely used in a variety of applications such as surveillance, control, and tracking [1]. Typically, a WSN involves a large number of wireless sensor nodes, each with a computational power and sensing capability. In such context, the problem of efficiently transmitting or sharing information from a vast number of distributed devices (nodes) makes a great challenge to the energy consumption and deployment cost which are the main constraints in WSN applications. As the number of WSN applications grows, the measure accuracy improvement and life time prolongment in WSN are essential. This is true especially for large scale networks. New mechanisms should then be deployed in order to optimize the cost, power, and traffic while guaranteeing good detection and estimation performance. It has recently been proved that Compressed Sensing (CS) theory holds promising improvements to the WSN system efficiency. Its potentials are those of minimizing the number of measurements required for field recovery from $N$ to $M$ ($M \ll N$) which can reduce the energy consumption as well as deployment and global scale communication costs within the network [2].

CS is simultaneously a new framework for signal sensing and a smart compression technique [3]. The fundamental idea, on which CS is based, is that any unknown signal having a sparse representation in some basis can be recovered from a small number of projections onto a second basis (known as sensing basis) which is incoherent with the first one [4].

In this work, the problem of events detection in WSN is investigated from the perspective of CS. To this aim, the sensed area is divided into a grid of cells; each cell is equipped with one sensor. We are here interested in the case of discrete events which are enumerated per cell. Also, a cooperative framework is considered, where events can be controlled from sensors. We interchangeably use “targets” for events and “nodes” for sensors throughout the paper.

Most of the existing work assumes that each cell contains at most one event [5] (binary event) which is not true in practice. Contrarily, as in [6], we here assume that one active cell can hold many events. Using CS recovery algorithms, both the locations and the number of events can then be recovered. A novel Greedy Matching Pursuit (GMP) algorithm [6] is considered which adapts the Matching Pursuit (MP) [7] algorithm to the discrete nature of events number.
Successful CS application for events positioning and counting requires two key features: sparsity and incoherence. The sparsity is here fulfilled in the spatial domain as the events to detect are assumed to be rare. Such scenario occurs in several applications such as animals tracking in forests and environmental factors detection such as fire and earthquake. As a consequence of rareness, the number of active cells (cells where events occur) is much lower than the network cells number. The CS theory then allows for recovering the events location and number by using only a small subset of the sensors measurements.

On the other hand, and related to the incoherence feature, a widely used condition on the sensing matrix ensuring a unique and accurate reconstruction of the sparse parameter (here, the vector of events number per cell) is the Restricted Isometry Property (RIP) [8] which gives guarantees concerning unique identifiability. Nevertheless, checking whether a sensing matrix $\Phi$ is RIP has a high combinatorial complexity. Closely connected to RIP, the coherence evaluation of the sensing matrix also characterizes the reconstruction performance. To optimize the sensing matrix choice, its construction is randomized. Some studies established that if the sensing matrix entries are independent and identically distributed (i.i.d.), then it verifies RIP with high probability under mild conditions [9]. In WSN context, the sensing matrix depends on the network topology through sensors locations and does not necessarily satisfy the last CS assumption. In the considered cooperative context, we then propose a transmit power control mechanism to force the sensing matrix to approximately obey the i.i.d. entries distribution hypothesis in such a way to approach RIP conditions and thus to guarantee a reduced coherence and consequently a good reconstruction performance.

This paper is organized as follows. In Section 2, the problem formulation for CS based events detection and counting is established. After introducing the CS application in WSN, the proposed mechanism based on transmitted power control (PC) is presented in Section 4. Finally, simulation results are drawn and analyzed in Section 5 before the conclusion.

Notations. Throughout this paper, we use the following notations: $(\cdot)^T$, $(\cdot)^H$, $(\cdot)^*$, and $E(\cdot)$ stand for the transposition, Hermitian, conjugate, and the expectation operator, respectively. Matrices are denoted by bold capital letters, whereas vectors are indicated by lowercase bold letters. If $A$ is a given matrix, we refer by $A_i$ and $A_{ij}$, respectively, to the $i$th column and the $(i, j)$th entry of $A$.

2. Model Description and Motivation

2.1. Network Model and Assumptions. We consider the WSN system model where the monitored area is divided into $N$ regular cells. We denote by $s$ the vector stacking the number of events of the $N$ cells. For $i = 1, \ldots, N$, $s_i \in \{0, \ldots, m\}$ meaning that the number of events each cell can hold is upper bounded by $m$. In our work, we assume that the cells where some events may occur are rare. This implies that only a reduced number of $K$ cells, among the total number of cells, $N$, contain events with $K \ll N$. These cells are referred to as active cells and verify $s_i > 0$.

In the following, we precise the adopted assumptions:

(i) $\mathcal{H}_0$: the different events transmitted signals are uncorrelated.

(ii) $\mathcal{H}_1$: the locations of the sensor nodes are fixed and a priori known. One sensor node is placed at each cell center to detect the events within its range and to contribute in their counting per cell.

(iii) $\mathcal{H}_2$: the vector $s$ containing the events number per cell is $K$-sparse and stationary in time, which, respectively, means that events are rare in the spatial domain and supposed to be constant (in position and number) during the processing time.

(iv) $\mathcal{H}_3$: the set of events occurring in the same cell are assumed to be spatially uniformly distributed within the cell. In the adopted model, the distance separating one event from its cell center is taken as a constant equal to $d_{\text{mean}}$, the mean possible distance in $[0.1, 1]d/2$, where $d$ is the distance between two adjacent sensors. The distance separating these events from the other cells sensors is of the order of the distance separating the corresponding sensors (cells centers).

As shown in Figure 1, the cell $i$ three events $i_k$ ($k = 1, 2, 3$) are at the same distance with respect to the sensor $i$ such that $d_{iij} = d_{ij} = d_{ijk}$. We take into account that, for cells $i \neq j, d_{iij} \gg d_{ij}, k \in \{1, 2, 3\}$. Then, we can write in a general manner that $d_{iij} = d_{ij}$ for $k = 1, \ldots, s_i$, where $d_{ij}$ denotes the distance between sensors $i$ and $j$.

(v) $\mathcal{H}_4$: channels between pairwise sensors are supposed to be Rayleigh block fading with known response. From $\mathcal{H}_3$, we also assume that the channels between one-cell events and another sensor outside the cell are the same as the channel between the corresponding sensors. This is in particular true in the scheme where each sensor retransmits its cell events signals to the network. Channels from different cells to a third one are supposed to be uncorrelated.

2.2. Problem Formulation. In large scale WSN, the propagation model should account for both path loss and Rayleigh fading effects. In this way, the received signal at sensor $j$ corresponding to targets located in an active cell $i$, with $s_i$ events, is given by

$$z_{ij} = \sum_{k=1}^{s_i} h_{ij} g_{ij}^{\frac{1}{2}} g_{i}^{\frac{1}{2}},$$

where $h_{ij}$ is the channel between the $i$th cell $k$th event and sensor $j$, which is a Rayleigh fading coefficient modeled as a complex Gaussian noise with zero mean and unit variance, $d_{ij}$ the distance between the $i$th cell $k$th event and
the sensor \( j \), and \( g_{ij} \) is the signal generated by the \( i \)th cell \( k \)th event which is modeled as complex Gaussian variable with zero mean and variance equal to \( P_0 \). Note that if cell \( i \) is inactive, then \( s_i = 0 \) and \( z_{ij} = 0 \). The coefficient \( \alpha \) denotes the path loss exponent related to the environment density [10]. In our work, \( \alpha \) describes the free space and is taken equal to 2. Let \( c_i = [h_{ij}^R/e_{ij}^R, \ldots, h_{ij}^N/e_{ij}^N] \) and \( \bar{g}_i = [g_{i1}, \ldots, g_{in}] \); then, \( z_{ij} \) can be written as

\[
z_{ij} = c_i^T \bar{g}_i.
\]  

Let \( \bar{x} \) denote the measurements from the \( N \) sensors. The total received signal at sensor \( j \), corrupted with noise and obtained by summing up the received signals from all cells, is expressed as

\[
x_j = \sum_{i \in \mathcal{S}} c_i^T \bar{g}_i + \eta_j,
\]

where \( \mathcal{S} \) denotes the set of active cells in monitored area and \( \eta_j \) is complex Additive White Gaussian Noise (AWGN) distributed as \( \eta_j \sim \mathcal{C} \mathcal{N}(0, \sigma^2) \). The additive noise is spatially uncorrelated such that \( E(\eta_j \eta_k^*) = \sigma^2 \delta_{jk} \), where \( \delta_{jk} \) is the Kronecker coefficient and is uncorrelated with the targets signals \( g_{ij} \).

Concatenating all sensors measurements, we have in matrix form

\[
x = C \bar{g}^T + \eta^T,
\]

where \( C \) is \( N \times N_{\text{tot}} \) channel matrix, where \( N_{\text{tot}} = \sum_{i=1}^N s_i \) is the total number of the grid events constructed as

\[
C = \begin{pmatrix} c_{11} & c_{21} & \cdots & c_{N1} \\
c_{12} & c_{22} & \cdots & c_{N2} \\
\vdots & \vdots & \ddots & \vdots \\
c_{1N} & c_{2N} & \cdots & c_{NN} \end{pmatrix}.
\]

\( \bar{g} = [\bar{g}_1, \ldots, \bar{g}_N] \) is \( 1 \times N_{\text{tot}} \) and denotes the generated events signals in the monitored area and \( \eta = [\eta_1, \ldots, \eta_N] \) is the noise component.

The autocorrelation matrix of the signal \( x \) is expressed as

\[
E xx^H = E \left( C \bar{g}^T \bar{g}^\ast C^H + \eta \eta^\ast \right).
\]

The received signal energy vector for the whole sensors is given by the diagonal elements of \( E xx^H \).

For the \( j \)th sensor, it is

\[
E (x_j x_j^\ast) = \sum_{n \in \mathcal{S}} E \left( c_n^T \bar{g}_n^\ast g_{nj}^* \right) + E (\eta_j \eta_j^\ast).
\]

Using \( \mathcal{H}_a \), the different cells links channels are uncorrelated such that \( E(c_n^T g_{nj}^*) = 0 \) for \( n \neq m \), and considering the assumption \( \mathcal{H}_0 \) which implies that \( E(\bar{g}_n^T \bar{g}_m) = 0 \) for \( n \neq m \), we can write

\[
E (x_j x_j^\ast) = \sum_{n \in \mathcal{S}} E \left( c_n^T \bar{g}_n^\ast g_{nj}^* \right) + E (\eta_j \eta_j^\ast),
\]

Then, the last expression reduces to

\[
E (|x_j|^2) = \sum_{n \in \mathcal{S}} E \left( \frac{\eta_j^2}{d_{nj}^2} |g_{nj}|^2 \right) + \sigma^2.
\]

In practice, the sensors received energy is evaluated by replacing the expectation in the above expression by averaging over samples collected during a limited observation interval over which the channel is supposed to be unchanged (block fading channel). Also, we assume that all generated events are uncorrelated with the channel responses.

Referring to assumptions \( \mathcal{H}_3 \) and \( \mathcal{H}_4 \), for any sensor \( j \) and one cell \( n \) with \( s_n \) events, we have the same Rayleigh fading and the same distance \( h_{nj} = h_n \) and \( d_{nj} = d_n \) for \( k = 1, \ldots, s_n \).

Therefore,

\[
E (|x_j|^2) = P_n \sum_{k=1}^{s_n} \frac{|h_n|^2}{d_{nj}^2} + s_n + \sigma^2.
\]
Concatenating $E(|x_j|^2)$, for $j = 1, \ldots, N$, leads to the $N$ elements energy vector $\bar{x}$ which is written as

$$\bar{x} = \Phi s + \bar{\eta},$$

where $\Phi$ is a $N \times N$ target decay energy matrix given by

$$\Phi = P_0 \begin{pmatrix}
|d_{11}^2| & |d_{21}^2| & \ldots & |d_{N1}^2| \\
\vdots & \vdots & \ddots & \vdots \\
|d_{1N}^2| & |d_{2N}^2| & \ldots & |d_{NN}^2|
\end{pmatrix},$$

and $\bar{\eta} = \sigma^2 1_N$. Note that $d_{ii} = d_{\text{mean}}$ for $i = 1, \ldots, N$. In CS, the matrix $\Phi$ relating the measurement $\bar{x}$ to the sparse vector of interest $s$ is called sensing matrix.

CS is an emerging theory that is based on the fact that a signal with a sparse representation in a certain basis can be recovered through a relatively small number of projections which contain the most of its information. The CS framework is here used in the aim of events detection and counting. Once the WSN energy measurements are available at the fusion center, the goal is to accurately locate the events occurrence and their number per cell. This is obviously operated under the constraint of power consumption and deployment cost reduction for network lifetime maximization. To achieve such aims, CS theory has proved to be well adapted. Indeed, CS can be applied to the problem of rare events detection in WSN and allows for reducing the number of required measurements from $N$ to some $M$ such as $M \ll N$. Indeed, with the parameter $s$ of interest being a sparse representation of $\bar{x}$ in the channel matrix basis $\Phi$ (refer to (11)), only $M \ll N$ nodes measurements are sufficient to recover $s$. In this way, $M$ linear combinations of $\bar{x}$ are used through a measurement matrix $\Psi$ for $s$ recovery. To reduce the power consumption in WSN, we choose a random selection matrix $\Psi$ as the measurement matrix to pick $M$ among $N$ sensors to be active. Mathematically, this selection can be expressed as

$$\begin{align*}
y &= \Psi \bar{x} = \Psi \Phi s + n, \\
y &= A s + n,
\end{align*}$$

where $\Psi$ is a $M \times N$ selection matrix, $A = \Psi \Phi$, and $n = \Psi \bar{\eta}$ is a subvector of $\bar{\eta}$. If not mentioned otherwise, the selection matrix $\Psi$ is randomly chosen.

Our objective is to reconstruct the sparse representation $s$ from the measurement vector $y$ knowing the matrix $A$. Then, under some conditions that will be handled later, $s$ can be accurately recovered from using CS reconstruction techniques. Recently, a family of iterative algorithms received significant attention due to their good tradeoff between complexity and performance. In this work, we envisage the iterative Greedy Matching Pursuit (GMP), which is an adapted version of the well known MP algorithm [7]. The iterative scheme GMP has been successfully applied in WSN to jointly identify the active cells and count their number of events in the detected cell in each iteration [6]. Then, the residual observation is updated accordingly. The algorithm terminates when no cells that contain at least one target are found.

Concerning the data collection task at the fusion center (for processing purpose), different schemes can be envisaged. The data $x_j$ sensed by sensor $j$, $j = 1, \ldots, N$, can be, for example, gathered to the fusion center using a mobile collection robot [11]. Also, we can adopt a deterministic access such as the Frequency or Time Division Multiple Access (FDMA, TDMA) where, over each frequency subband or during each time slot, one sensor can broadcast and transmit its data (energy measurements through the network). This supposes a perfect synchronization and reliable communication [12, 13]. Also, the deployed sensors readings can be transmitted simultaneously to the sink in the case of the sink knowledge of the different links and the independence between these links.

2.3. Motivation. As stated in CS theory, a sufficient condition for the successful recovery of a sparse signal is that the decomposition basis $A$ obeys the Restricted Isometry Property (RIP) [8]. In practice, random matrices with i.i.d. entries are commonly used as measurement matrices and are known to have a low coherence with any sensing matrix $\Phi$ [3, 14, 15] which verify the RIP with high probability. Examples of such random matrices include matrices with elements following Gaussian distribution with zero mean and variance $1/M$ [16]. However, in the WSN context, as mentioned earlier, in order to reduce power consumption, the measurement matrix $\Psi$ is chosen as a selection matrix making $A$ keep the same properties as $\Phi$. The latter indeed depends on the sensors locations through distance $d_{ij}$ which violates the i.i.d. assumption and might produce high data recovery error. The channel model adopted in our context of large scale WSN accounts for both Rayleigh and path loss fading effects, representing the signal attenuation caused, respectively, by local scatterers and by distance. In a small scale WSN, path loss effect can be neglected, which corresponds, at the model level, to setting the path loss exponent $\alpha$ to 0. In this case, matrix $\Phi$ (12) entries are i.i.d. and thus it verifies RIP with high probability. This observation suggests that, in order to better satisfy RIP in large scale WSN, for which path loss cannot be neglected, the location effect, which appears through distance terms at power $\alpha$ in matrix $A$ (14), should be compensated for to reduce its coherence.

In the following, we illustrate the impact of the decomposition matrix characteristics on the recovery performance. To this end, we consider a comparison between four scenarios differing by the sensing matrix $\Phi$:

(i) Perfect compensation of distance (exclusively Rayleigh effect), $\Phi_{ij} = P_0|\beta_{ij}|$, which corresponds to $\alpha = 0$.

(ii) $\Phi$ of (12) with adjacent sensors spacing of $d = 5$ m, $d = 10$ m, and $d = 20$ m.

The corresponding GMP reconstruction performance is evaluated in terms of reconstruction error by Normalized
Mean Squares Error (NMSE) on $s$ and on active cells positions detection, independently of the estimated events number (NMSE$_p$). The error in position detection accounts for both missing (undetected active cell) and false alarm (erroneously detected cell where there are no targets). The chosen performance evaluation criteria NMSE$_s$ and NMSE$_p$ are, respectively, given by:

$$\text{NMSE}_s = \frac{E(\|s - \hat{s}\|_2^2)}{E(\|s\|_2^2)}, \quad (15)$$

where we indicate by $s$ and $\hat{s}$ the vectors that concatenate true and estimated number of events per cell:

$$\text{NMSE}_p = \frac{E(\|z - \hat{z}\|_2^2)}{E(\|z\|_2^2)}, \quad (16)$$

where $z$ and $\hat{z}$ are binary vectors obtained, respectively, from $s$ and $\hat{s}$ by placing 1 at nonzero valued entries locations and 0 otherwise. We also consider a measure of coherence which is more likely to describe the performance of the proposed mechanisms in approaching the RIP conditions guaranteeing decomposition accuracy and uniqueness. For a given dictionary $A$, its mutual-coherence is defined as the largest absolute and normalized inner products between different columns in $A$ as follows:

$$\mu(A) = \max_{i<j \in \{1,\ldots,N\}} \frac{\|A_i^T A_j\|_2}{\|A_i\|_2 \|A_j\|_2}. \quad (17)$$

This $\mu$ value provides a measure of the worst similarity between the dictionary columns.

For the same cells number, $N$, we then envisage small and then medium to large scale networks.

According to Figure 2 displaying the NMSE$_s$ on sparse signal $s$, versus Signal Noise to Ratio (SNR) defined as SNR = $P_0/\sigma^2$, it is noticed that the path loss fading seriously affects the reconstruction rate which leads to a high targets recovery error. Then, the larger the WSN is, the bigger the reconstruction error is. The Rayleigh scenario (with $\alpha = 0$) achieves the lowest recovery error which coincides with the smallest coherence value reaching $0.8951$ compared to $0.9902$ with the large scale scenario (Rayleigh and path loss fading).

Also, Table 1 shows that the coherence value is not as much sensitive to the spacing between sensors as is the NMSE, depicted in Figure 2.

Further, a coherence reduction is shown to guarantee a more accurate recovery. Therefore, in order to enhance reconstruction accuracy, we propose to control the transmitted power of targets in order to compensate the path loss and to make $A$ better approach an i.i.d. Gaussian matrix.

**Table 1: Coherence comparison.**

| Scenario | $d = 20$ m | $d = 10$ m | $d = 5$ m | Optimal |
|----------|------------|------------|------------|---------|
| Coherence | 0.9902     | 0.9903     | 0.9903     | 0.8951  |

The performance is evaluated in terms of NMSE$_s$, and NMSE$_p$ given, respectively, by (15) and (16). Also, the missing and false alarm rates are illustrated.

Reference [17] also addressed the problem of cooperative power control in WSN. It proposed a method for proper matrix $A$ design to achieve a sufficiently low coherence and guarantee a good recovery performance. Different models for the sensing matrix are adopted and PC schemes are proposed accordingly. Two key parameters $d_m$ and $d_M$ are optimized in order to minimize both decomposition matrix coherence and channel estimation cost. $d_m$ is the PC region radius relatively to any sensor or cluster head (CH). Indeed, the processing is composed in periods. In each period, one sensor is considered as a cluster head (CH) or a reference node and applies PC for the network. $d_M$ denotes the CH coverage (further nodes do not transmit). We hereafter compare the performance of the above cited “existing work” to those of Rayleigh fading ($\alpha = 0$) and case without PC, referred to as w.o.PC (all of which account for the sensors maximum coverage range). We choose $d_M = d_{\text{max}}$ the coverage range and $d_m$ equal to the mean distance of the nodes within the coverage to the considered CH (refer to Figure 3).

The performance is evaluated in terms of NMSE$_s$ and NMSE$_p$ given, respectively, by (15) and (16). Also, the missing and false alarm rates are illustrated.

The obtained results are given by Figure 4 and show that the referenced work achieves a high NMSE and missing and false alarm rates especially at low SNR compared to the case w.o.PC. This scheme outperforms the case w.o.PC above $35$ dB and for this reason will not be further considered in the rest of the paper. Also, Figure 4 shows that the reconstruction and detection performance of the benchmark scheme (Rayleigh fading) are not very sensitive to noise, which is indeed due to the Rayleigh fading effect dominance.

In the following, we consider large scale WSN and low to medium SNR range (SNR $\leq 30$ dB).
Table 2: Comparison between referenced and proposed approaches.

| Criterion/approach       | Existing work          | Proposed approach       |
|--------------------------|------------------------|-------------------------|
| Cells partition          | Range                  | Range or number         |
| Repartition parameters   | Cost of power and channel estimation | Coverage |
| Compensation             | Local                  | Local or global         |
| PC                       | Reduce power of neighboring targets according to their range from the sensor | Increase or reduce power per class of nodes |

Figure 3: Power control model [17]. Only the nodes inside the radius \(d_m\) have power control.

This paper proposes new power control schemes whose accurate comparison to the existing work [17] is given in Table 2. Two new approaches are here proposed and compared, which are, respectively, based on sensors spatial repartition and sensors number.

4. Proposed Approaches for Power Control

4.1. Framework Overview. In our work, we envisage a sub-optimal power control based on distance compensation per subsets of cells (or clusters) which accounts for the sensors maximum coverage (range) \(d_{\text{max}}\). In this way, only the nodes inside the coverage zone transmit. Note that, as a result of the sensors limited coverage, the energy saving by canceling the transmissions of the out of coverage targets leads to a sensing matrix with some zero valued coefficients which may pejoratively impact the RIP condition. In this context, we envisage a comparison between two coverage values corresponding to Zigbee [18, 19] and WiFi [20] standards based, respectively, on IEEE 802.15.4 and IEEE 802.11. We consider the case of regular large scale WSN with \(N = 64\) and \(d = 20\) m. The envisaged Zigbee and WiFi protocols used to insure the devices interconnection have respective ranges \(d_{\text{max}}\) of 100 m and 300 m. With WiFi protocol, the network is fully recovered; that is, all targets nodes are detectable by the considered CH. We denote this case as High Coverage Sensors (HCS) since the coverage includes the whole network, whereas the Zigbee scenario, where only a part of network is recovered by the reference node, is referred to as Low Coverage Sensors (LCS). We envisage both HCS (as in WiFi) and LCS (as in Zigbee) in case w.o. PC processing. Examining the detection curves displayed in Figure 5, we note that HCS achieves a slightly higher detection rate compared to LCS scenario. This is in concordance with the coherence measure displayed in Table 3 which is slightly lower for HCS case. The small difference between both considered scenarios is due to the fact that, with the path loss being very severe outside the coverage region, the corresponding received signals are so attenuated that they approach the case where the targets outside the maximum coverage do not transmit.

In the following, we focus on large WSN and account for the sensors coverage. More precisely, the Zigbee protocol (LCS) will be considered.

Actually, the coverage range \(d_{\text{max}}\) is related to the sensors sensitivity and to the maximal transmitted targets power \(P_{\text{max}}\). As mentioned above, \(P_0\) denotes the targets transmitted power which in fact depends on the network dimensions and the sensors sensitivity. Indeed, \(P_0\) corresponds to the coverage \(d_0\).

Referring to the power law model [21], let \(\epsilon\) denote the lowest perceivable power by the sensors (the threshold or minimum value of the process required to obtain a nonzero output); then, \(\epsilon\) depends on the maximal power and on its corresponding maximal coverage \(d_{\text{max}}\) as follows:

\[
\epsilon = \frac{P_{\text{max}}}{d_{\text{max}}} q, \quad \text{where } q \text{ is a constant.} \tag{18}
\]

(18)

The choice of \(P_0\) in the scheme w. PC indeed depends on the targeted coverage radius \(d_0\). According to the chosen value of \(d_0\) with \(d_0 \leq d_{\text{max}}\), the transmission power will be

\[
P_0 = P_{\text{max}} \left(\frac{d_0}{d_{\text{max}}}\right)^\alpha. \tag{19}
\]
The choice of $d_0$ (or equivalently $P_0$) will be analyzed in Section 5.2.

We propose in the following to control the transmitted power of nodes within the maximal coverage zone with radius $d_{\text{max}}$. As a benchmark, we consider the scheme w.o.PC in which all nodes within the coverage $d_0$ of one sensor transmit with power $P_0$ and the targets outside this coverage region $d_0$ remain in sleep mode (do not transmit). This principle is illustrated by Figure 6 and the required transmit power of targets can be presented as

$$ P_0 \quad d_{ij} \leq d_0 $$

otherwise.

4.2. Scenario Description. For reconstruction performance enhancement, we aim to reduce the coherence of the sensing matrix $A$. To this end, we control the transmit power of targets. The power control scheme allows for compensating the distance separating the sensor device and the target location throughout the network. More precisely, it increases the transmit power for the farthest targets to compensate their fading and reduces the power for the nearest targets to CH. Note that in [17] the nearest nodes are assigned reduced transmit power and the farthest do not undergo any PC and keep their initial transmit power.

In our study, we consider a time division multiplexing scheme where the time is divided into packets of $M$ slots as shown in Figure 7, where $P(i, j)$ is the transmission power after PC of cell $i$ targets when the sensor $j$ listens, $i \in 1, \ldots, N$.
and $j \in 1,\ldots,M$. For time slot $j$, node $j$ listens, computes $P(i,j)$ for $i = 1,\ldots,N$, and communicates it to the network allowing for PC; sensor $j$ then measures power after PC. Reconstruction is then processed after all $M$ sensors energy measurements collection.

We here propose two approaches for power control, both of which consider a spatial partition of nodes with respect to a reference node (CH). Contrarily to the perfect PC where each node has a perfect compensation of path loss effect, in our work, motivated by total power consumption reduction, the PC is operated by subgroups of nodes. These subgroups are formed either based on their proximity to the reference node (approach 1: distance- (range-) based) or based on their spatial density (approach 2: sensors number). This partition results in rings (uniform for range-based partition).

For each of range and number based approaches, two schemes are envisaged, which are, respectively, global and local schemes. In global approach, the power control is done per class, or cluster, of nodes where the same transmitted power is allocated to the nodes belonging to the same ring. In local approach, the power control considers both the node distance from CH and the ring to which it belongs. In the following two sections, these proposed approaches are detailed.

4.3. Proposed Power Control Mechanism Based on Distance (PCMD). This approach is based on the sensors maximum range, $d_{\text{max}}$, which depends on the sensors sensitivity. Also, we denote by $P_{\text{max}}$ the maximum power which can be delivered by the targets. $d_{\text{max}}$ and $P_{\text{max}}$ are supposed to be uniform for all sensors and targets. The target is not detectable by the CH when the distance between them exceeds $d_{\text{max}}$. Such case, the CH sets the transmitted power to zero (corresponding targets do not need to transmit).

Our approach attempts to compensate the energy attenuation caused by distance. First, we consider only the cells (sensors) within the coverage of the corresponding CH, that is, situated at a distance lower than $d_{\text{max}}$. Then, we divide this set in $n$ subsets with $1 \leq n \leq N_1$ ($N_1$ being an upper bound to prevent empty sets and is related to the ratio between $d_{\text{max}}$ and adjacent sensors spacing $d$). Each subset $k$ contains the sensors lying within a ring delimited by the two circles centered on the CH and of respective radii $R_{k}^{(0)}$ and $R_{k+1}^{(0)}$ such that

$$R_{k}^{(0)} = k \frac{d_{\text{max}}}{n}, \quad n = 1,\ldots,N_1, \quad 1 \leq k \leq n,$$  \hspace{1cm} (21)

where $R_{n}^{(0)}$ corresponds to $d_{\text{max}}$.

This mechanism performs with two manners: in a global manner for which the scheme is denoted PCMDg, or in a local manner for which the scheme is named PCMDl. In the following, the two proposed schemes are developed.

4.3.1. PCMDg. In this part, we propose to globally compensate for the distance effect: the nodes within the same ring are allocated the same transmission power. In the following, we will discuss the cases $n = 1$ and $n = 2$. The scheme is then generalized to greater values of subsets $n$ corresponding to a finer spatial partition.

(i) $n = 1$. As mentioned above, the CH can hear only the nodes within the coverage $d_0$. Then, we propose to amplify the transmitted power of the targets outside the ring with radius $d_0$ and at the same time within the range $d_{\text{max}}$. Therefore, the components of power control matrix, $P(i,j)$, denoting the required transmit power of targets situated in cell $i$ controlled by sensor $j$ can be presented as

$${P(i,j)} = \begin{cases} P_0 & {d_{ij} \leq d_0} \\ P_{\text{max}} & {d_0 < d_{ij} \leq d_{\text{max}}} \\ 0 & {d_{ij} > d_{\text{max}}} \end{cases} \quad (22)$$

(ii) $n = 2$. The power control is based on the partition described in Figure 8 where the CH coverage is partitioned into two concentrated circular regions. The components of power control matrix, $P(i,j)$, can be expressed as

$${P(i,j)} = \begin{cases} P_0 & {d_{ij} \leq R_1^{(2)}} \\ P_1 & {R_1^{(2)} < d_{ij} \leq d_{\text{max}}} \\ 0 & {d_{ij} > d_{\text{max}}} \end{cases} \quad (23)$$

verifying $P_0/R_1^{(2)} = P_1/d_{\text{max}}$, which leads to $P_1 = P_0 (d_{\text{max}}/R_1^{(2)})^\alpha = P_0 (R_1^{(0)}/d_0)^\alpha$.

(iii) General Case. Generalizing the schemes described above for $n = 2$ to larger values of $n \geq 2$, the form of the power matrix is given by

$${P(i,j)} = \begin{cases} P_0^{(n)} & {d_{ij} \leq R_1^{(n)}} \\ P_1^{(n)} & {R_1^{(n)} < d_{ij} \leq R_{n+1}^{(n)}} \\ 0 & {d_{ij} > d_{\text{max}}} \end{cases} \quad (n\geq 2), \quad l = 0,\ldots,n-1 \quad (24)$$

such as

$$P_0 = P_0^{(n)}, \quad R_1^{(n)} = (R_1^{(0)}/d_0)^\alpha, \quad R_1^{(n)} = P_0^{(n)} \left( \frac{P_0^{(n)}}{d_0} \right)^\alpha \quad (25)$$

Let us note that, according to the ratio $R_1^{(n)}/d_0$, the controlled power can be larger or lower than $P_0$.

4.3.2. PCMDl. In this part, a local distance compensation is considered: each node is affected by a different transmission power according to its position. We keep the same notation presented in the PCMDg. Also, the cases $n = 1$ and $n = 2$ will be presented before generalizing to higher orders of $n$. 

![Figure 7: Scenario description.](image-url)
For the nodes outside the coverage zone with radius $d_{\text{max}}$, no signal is transmitted by the cell targets.

(i) $n = 1$. In this case, we locally compensate the distance for the targets within the coverage $d_0$. Then, the components of power control matrix $P$ are presented as

$$P(i, j) = \begin{cases} 
    P_0 \left( \frac{d_{ij}}{d_0} \right)^\alpha & d_{ij} \leq d_0 \\
    P_{\text{max}} & d_0 < d_{ij} \leq d_{\text{max}} \\
    0 & d_{ij} > d_{\text{max}}.
\end{cases}$$  \hspace{1cm} (26)

(ii) $n = 2$. The components of power control matrix $P$ are expressed as

$$P(i, j) = \begin{cases} 
    P_0 \left( \frac{d_{ij}}{d_0} \right)^\alpha & d_{ij} \leq R^{(2)}_1 \\
    P_{\text{max}} & R^{(2)}_1 < d_{ij} \leq d_{\text{max}} \\
    0 & d_{ij} > d_{\text{max}}.
\end{cases}$$  \hspace{1cm} (27)

(iii) General Case. The previous development can be generalized as follows:

$$P(i, j) = \begin{cases} 
    P_0 \left( \frac{d_{ij}}{d_0} \right)^\alpha & d_{ij} \leq R^{(n)}_{n-1} \\
    P_{\text{max}} & R^{(n)}_{n-1} < d_{ij} \leq d_{\text{max}} \\
    0 & d_{ij} > d_{\text{max}}.
\end{cases}$$  \hspace{1cm} (28)

4.4. Proposed Power Control Mechanism Based on Sensors Number (PCMSn). The last approach proposed in Section 4.3 partitions the nodes into subsets with respect to the distance separating them from the CH as a fraction of the sensor coverage region radius $d_{\text{max}}$. Differently, we now consider a partition of the nodes which splits them into subsets still contained in the same ring centered on the CH but with a further constraint that the rings have equal number of nodes. This partition changes according to the deployed sensors density in the monitored area. First, we sort the sensors according to the distance separating them from CH $j$, in an ascending order (from the nearest to the farthest). For any CH $j$, this sorting corresponds to considering $\{\tilde{d}_{ij}\} = \{d_{ij}\}$ such that $\tilde{d}_{ij} \leq \tilde{d}_{i+1,j}$, for $i = 1, \ldots, N - 1$. Then, the network is divided into $n$ collections.

Like the distance-based PC, two ways can be envisaged for PCMSn scheme: global way which is denoted PCMSng and local way referred to as PCMSnl. In the following, we will limit the discussion to the case $n = 2$ and even if it is not included in this work, this mechanism can be further generalized to larger values for both PCMSng and PCMSnl approaches.

In this case, for each sensor $j$, taken as CH, we divide the sensors network into two sets: the first set contains the $N/2$ closest sensors to the sensor $j$ as shown in Figure 9. The remaining $N/2$ sensors form the second set. Let $d_{m}^{(1)}$ and $d_{m}^{(2)}$ denote, respectively, the mean distance of the two groups such as

$$d_{m}^{(1)} = \frac{2}{N/2} \sum_{i=1}^{N/2} \tilde{d}_{ij},$$  \hspace{1cm} (29)

$$d_{m}^{(2)} = \frac{2}{N} \sum_{i=N/2+1}^{N} \tilde{d}_{ij}.$$
As already considered above, targets outside the CH \( j \) coverage remain silent (do not transmit). The global and local schemes are hereafter detailed for \( n = 2 \).

4.4.1. PCMSng. This scheme is based on global compensation of distance. Indeed, we will associate the same transmitted power for a subset of sensors.

**Case 1** \((d_m^{(2)} \leq d_{\text{max}})\). The components of power control matrix can be presented as

\[
P(i, j) = \begin{cases} 
P'_0 \ (d_m^{(1)})^\alpha & d_{ij} \leq d_m^{(1)} \\
p'_1 \ (d_m^{(1)})^\alpha < d_{ij} \leq d_m^{(2)} \\
p'_2 \ (d_m^{(2)})^\alpha < d_{ij} \leq d_{\text{max}} \\
0 & d_{ij} > d_{\text{max}} \end{cases}
\]

with

\[
P'_0 = P_0 \left(\frac{d_m^{(1)}}{d_0}\right)^\alpha.
\]

In order to compensate the path loss effect and to verify the RIP criterion, the sensing matrix \( \mathbf{A} \) components should at the best fit the i.i.d. entries model. To this end, the PC values are chosen as

\[
\frac{P'_0}{(d_m^{(1)})^\alpha} = \frac{P'_1}{(d_m^{(2)})^\alpha} = \frac{P'_2}{d_{\text{max}}^{\alpha}}.
\]

which leads to the power values,

\[
P'_0 = P_0 \left(\frac{d_m^{(1)}}{d_0}\right)^\alpha,
\]

\[
P'_1 = P_0 \left(\frac{d_m^{(2)}}{d_0}\right)^\alpha,
\]

\[
P'_2 = P_0 \left(\frac{d_{\text{max}}}{d_0}\right)^\alpha = P_{\text{max}}.
\]

**Case 2** \((d_m^{(1)} < d_{\text{max}} < d_m^{(2)})\). Consider

\[
P(i, j) = \begin{cases} 
P'_0 \ (d_m^{(1)})^\alpha & d_{ij} \leq d_m^{(1)} \\
p'_1 \ (d_m^{(1)})^\alpha < d_{ij} < d_m^{(2)} \\
p'_2 \ (d_m^{(2)})^\alpha < d_{ij} \leq d_{\text{max}} \\
0 & d_{ij} > d_{\text{max}} \end{cases}
\]

**Case 3** \((d_m^{(1)} > d_{\text{max}})\). We seek to find the targets positions \( i \) with distance \( d_{ij} \leq d_{\text{max}} \). Then, we compute the mean distance of sensors locations within the coverage zone denoted by \( d_m^{(0)} \). The components of corresponding power control matrix \( \mathbf{P}(i, j) \) can be expressed as

\[
P(i, j) = \begin{cases} 
P'_0 \ (d_m^{(0)})^\alpha & d_{ij} \leq d_m^{(0)} \\
p'_1 \ (d_m^{(0)})^\alpha < d_{ij} < d_m^{(2)} \\
p'_2 \ (d_m^{(2)})^\alpha < d_{ij} \leq d_{\text{max}} \\
0 & d_{ij} > d_{\text{max}} \end{cases}
\]

4.4.2. PCMSnl. In this part, a local distance compensation is adopted. The case \( n = 2 \) is described hereafter.

**Case 1** \((d_m^{(2)} \leq d_{\text{max}})\). The components of power control matrix can be presented as

\[
P(i, j) = \begin{cases} 
P'_0 \ (d_m^{(1)})^\alpha & d_{ij} \leq d_m^{(2)} \\
p_{\text{max}} \ (d_m^{(2)})^\alpha < d_{ij} \leq d_{\text{max}} \\
0 & d_{ij} > d_{\text{max}} \end{cases}
\]

**Case 2** \((d_m^{(1)} < d_{\text{max}} < d_m^{(2)})\). Consider

\[
P(i, j) = \begin{cases} 
P'_0 \ (d_m^{(1)})^\alpha & d_{ij} \leq d_m^{(1)} \\
p_{\text{max}} \ (d_m^{(1)})^\alpha < d_{ij} \leq d_{\text{max}} \\
0 & d_{ij} > d_{\text{max}} \end{cases}
\]

**Case 3** \((d_m^{(1)} > d_{\text{max}})\). The corresponding PC procedure is as follows:

\[
P(i, j) = \begin{cases} 
P'_0 \ (d_m^{(0)})^\alpha & d_{ij} \leq d_m^{(0)} \\
p_{\text{max}} \ (d_m^{(0)})^\alpha < d_{ij} \leq d_{\text{max}} \\
0 & d_{ij} > d_{\text{max}} \end{cases}
\]

The previous steps for both global and local PC can be generalized for \( 2 < n \leq N \), where the network is divided into \( n \) subsets with the same number of sensors per subset and respecting the deduced values of \( d_m^{(0)} \), \( l = 1, \ldots, n \).

Compared to perfect distance compensation, the above local scheme allocates \( P_{\text{max}} \) on the last coverage ring, thus leading on this ring to a slightly higher power than that required by perfect distance compensation (for both distance and sensors number based approaches).

4.5. Events Detection and Counting. Once the power control matrix \( \mathbf{P} \) is constructed according to one of the different previous PC mechanisms, the measured energy vector during the sensing period when PC is applied can be written as

\[
y = \frac{1}{P_0} \mathbf{P} \odot \mathbf{A} \mathbf{s} + \mathbf{n},
\]

where \( \odot \) is the element-wise product and matrix \( \mathbf{P} \) elements tune the targets transmission power according to the chosen PC scheme. Compared to (14) where no PC is used, the new decomposition matrix is \( \mathbf{A}' = \mathbf{P} \odot \mathbf{A} \) which is expected to better verify RIP and to have lower coherence. Note that (39) coincides with (14) for \( \mathbf{P} = P_0 \mathbf{I}_{M \times N} \). The performance study will then evaluate the accuracy of \( \mathbf{s} \) recovery from \( y \) measurement.

The adopted decomposition algorithm is the GMP which has the advantage not to require any knowledge about the signal sparsity level. In [6], the recently proposed iterative
5. Performance Evaluation and Analysis

5.1. Simulation Parameters Setting. The hereafter displayed results are obtained through Monte Carlo simulations based on the following setting. We consider a regular monitored area divided into \( N = 64 \) (8 by 8) cells. Among these \( N \) cells, \( K = 2 \) cells are active (where events occur). At each cell center, one sensor node is placed to detect events occurring in the network. The adjacent sensors spacing is \( d = 10 \) m. We deploy \( N \) sensors among which \( M = 20 \) are selected to be active (during the processing). The number of events occurring in the active cells is chosen uniformly at random from \( \{1, 2, 3\} \). As mentioned above, we consider Zigbee as a wireless protocol ensuring the interconnection between the devices [18, 19]. \( d_{\text{max}} \) and \( d \) values correspond to a control region covering a maximal radius of 5 cells. The power control parameters are described in Table 4.

This section aims to evaluate the efficiency of the different proposed PC mechanisms and their impact on the recovery and detection performance which is evaluated in terms of NMSE, and NMSE\(_{p}\), respectively, given by (15) and (16) for varying SNR values. We also consider a measure of coherence, given by (17), to characterize the proposed mechanisms capacity in approaching the RIP conditions.

The above proposed power control schemes adjust the power to be transmitted according to a mean distance (global) or the actual distance (local) from the CH. It is then of great interest to also evaluate for the proposed schemes the total amount of consumed power in the network denoted as \( P_{\text{tot}} \) and given by

\[
P_{\text{tot}} = \sum_{i=1}^{M} \sum_{j=1}^{N} P(i, j) s_j.
\]

In order to assess the proposed approaches relevance in terms of power saving, a quotient of the required power normalized to the case w.o.PC (described in Section 4.1) is envisaged.

Our considered benchmarks cases are w.o.PC and perfect PC in which we compensate locally and perfectly the distance of the corresponding target within the range \( d_{\text{max}} \).

5.2. Numerical Results. In this section, some numerical results will be presented showing the performance improvement obtained with each of the proposed PC approaches.

Table 5: Coherence and power consumption evaluations, benchmark approach.

| Criterion/approach | LCS scenario |
|--------------------|--------------|
| Cases              | w.o.PC       | Perfect PC |
| \( \mu \)          | 0.999        | 0.8964     |
| \( P_{\text{tot}} \) (mW) | 3.3          | 17.6       |
| Quotient (normalized to the case w.o.PC) | 1            | 5.33       |

Firstly, the coherence of the decomposition matrix \( A' \) (decomposition matrix with PC) and network total power are evaluated. Then, reconstruction and detection performance, in terms of NMSE, and NMSE\(_{p}\), are evaluated. Finally, a comparative study of all proposed PC approaches is carried with a further comparison to the cases w.o.PC and with perfect PC.

(i) Coherence and Required Power. Results are given in Tables 5–7, for different PC schemes, obtained by averaging over 500 Monte Carlo trials where Rayleigh fading and active cells (\( K \) among \( N \)) and sensors selection (\( M \) among \( N \)) are randomly generated.

Table 5 displays the results relative to benchmarks: perfect PC and w.o.PC. It shows that when comparing the two cases, a coherence reduction and yet higher power consumption are induced by perfect PC compared to w.o.PC. It can be noticed that perfect PC reduces coherence and increases power consumption with respect to case w.o.PC.

Tables 6 and 7, respectively, give results of PCMD and PCMSn schemes.

Table 6 shows for PCMD that both PCMDg and PCMDl lead to lower coherence than w.o.PC, yet higher than perfect PC. As the number of clusters \( n \) of cells used in PC processing is increased, the coherence decreases, for both global, except for \( n = 1 \) in which no spatial partition of cells is considered (refer to (22)), and local schemes. Also, for larger \( n \), the power consumption decreases for both global and local schemes. Compared to local processing, global processing leads to higher coherence and higher power consumption. The same observations hold for PCMSn scheme with results displayed in Table 7.

Finally, to summarize,

(i) in terms of power consumption, the case w.o.PC has the lowest value than perfect PC and finally proposed schemes consume the largest power,

(ii) in terms of decomposition matrix coherence, the least value is obtained by perfect PC and then by proposed PC schemes and finally the case w.o.PC has the largest coherence,

(iii) we note that, by increasing the cells repartition (\( n \)), the proposed PC schemes consume lower power and lead to smaller coherence converging to the perfect PC.

The criteria of power consumption and coherence evaluation are not sufficient to evaluate the different schemes relevance. Hereafter, we evaluate the recovery performance.

(ii) Detection and Counting. Figures 10–13 report, respectively, performance of PCMDg, PCMDl, PCMSng, and PCMSnl in

Table 4: Simulation parameters [18].

| Total number of sensors | \( N = 64 \) |
| Active sensors          | \( M = 20 \) |
| Active cells number (random) | \( K = 2 \) |
| Max range (Zigbee)     | \( d_{\max} = 100 \) m |
| Targeted coverage radius | \( d_o = 20 \) m |
| Max transmitted power   | \( P_{\max} = 1 \) mW |
Table 6: Coherence comparison and power consumption for PCMD approaches.

| Criterion/case | Approach | $n=1$ | $n=2$ | $n=3$ | $n=4$ |
|----------------|----------|-------|-------|-------|-------|
| $\mu$          | Global   | 0.9271| 0.9306| 0.9707| 0.9122|
|                | Local    | 0.9122| 0.9462| 0.8984| 0.9186|
| $P_{\text{tot}}$ (mW) | 68       | 67    | 40.2  | 32.5  | 21.1  |
| Quotient (normalized to the case w.o.PC) | 21.26   | 20.94 | 12.43 | 10.15 | 9.54  |

Table 7: Coherence comparison and power consumption for PCMSn approaches.

| Criterion/case | PCMSng | PCMSnl |
|----------------|--------|--------|
| $\mu$          | 0.9237 | 0.9100 |
| $P_{\text{tot}}$ (mW) | 32.9  | 28.1   |
| Quotient (normalized to the case w.o.PC) | 10.45 | 8.93   | 8.57  | 7.44  |

Figure 10: Performance evaluation for PCMDg approach.

terms of NMSE$_t$ and NMSE$_p$, obtained by GMP algorithm for varying number of clusters $n$ used for PC.

Figures 10(a) and 10(b) show performance enhancement when the levels number $n$ decreases. In fact, the case $n=1$ is the most efficient in terms of reconstruction achieving the best performance. Indeed, even if the coherence is reduced for larger $n$, power consumption decrease negatively affects the performance.

For all schemes, it is possible to achieve better performance than the case perfect PC which can be related to its reduced power consumption. The worst scheme is that of w.o.PC. The above performance comparison is elaborated for a given scenario by the definition of $(d_0, P_0)$ specifying designed coverage and corresponding transmission power. Applying different PC schemes leads to modified transmission power according to spatial same coverage for all repartition of cells, making the obtained results relative to the consumed power. For a fair comparison, we hereafter consider an equal consumed power constraint in the following part. This difference between powers is induced by choosing the same coverage for all schemes.

(iii) Comparison between the Proposed Power Control Approaches. In this part, a comparative study of the different PC proposed schemes is carried. Two cases are envisaged: Case 1, where there is no constraint on the consumed power, and Case 2, where an equal consumed power is imposed for all schemes. The results are depicted in Figure 14 where solid lines correspond to Case 1 and dashed lines correspond to Case 2.

Case 1 (without constraint on power). In Case 1, we note that the best performance is achieved with the global PC mechanism since the scheme leads to the lowest reconstruction errors at low SNR range. From SNR = 25 dB, local schemes lead to the best performance. The perfect PC achieves slightly lower performance than local performance schemes above for all SNR range. This comparison is true for both performance criteria NMSE$_t$ and NMSE$_p$.

Case 2 (equal total power constraint). We here compare each PC scheme to the case w.o.PC while imposing their consumed power equality. In Figure 14, dashed curves correspond to processing w.o.PC when it uses the same power compared
Figure 11: Performance evaluation for PCMDi approach.

Figure 12: Performance evaluation for PCMSng approach.

to one of the PC schemes (solid line with the same symbol) when the latter has range $d_0$. Unifying PC schemes leads to $P^{sc}(i, j) = (L^{sc}(i, j)/d_0)^\alpha P_0$, where $L^{sc}(i, j)$ depends only on network topology and PC scheme $sc$ among PCMDg, PCMDl, PCMSng, and PCMSnl.

Respectively, for cases w.o.PC and with PC, the total consumed power is expressed as

$$P_{\text{tot}}^\text{w.o.PC} = MP_0 \sum_{j=1}^{N} s_j,$$

$$P_{\text{tot}}^\text{PC} = \sum_{i=1}^{M} \sum_{j=1}^{N} P^{sc}(i, j) s_j = \sum_{i=1}^{M} \sum_{j=1}^{N} \left( \frac{L^{sc}(i, j)}{d_0} \right) ^\alpha P_0 s_j.$$  

Imposing Equal Power (EP) constraint then leads, if PC scheme considers coverage $d_0$, to a transmission power $P_0^{\text{EP}}$ for the w.o.PC scheme such that

$$P_0^{\text{EP}} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (L^{sc}(i, j)/d_0)^\alpha P_0 s_j}{MP_0 \sum_{j=1}^{N} s_j},$$

corresponding to a coverage $d_0^{\text{EP}}$ such that

$$d_0^{\text{EP}} = \sqrt[\alpha]{\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (L^{sc}(i, j)/d_0)^\alpha s_j}{M \sum_{j=1}^{N} s_j}}.$$
In this way, according to $d_0$ and $d_{\text{max}}$, $d_{\text{EP}}$ can be larger or smaller than $d_0$, corresponding, respectively, to larger or smaller coverage compared to the considered PC scheme $s_c$. For example, for the case envisaged in the former detection performance study, imposing the same coverage leads to an increase of all the PC schemes consumed power with respect to the w.o.PC case and thus the r.h.s. of (44) is larger than 1 and a higher w.o.PC scheme coverage is obtained in this case under EP constraint. In the following, the coverage effect is studied by varying $d_0$.

(iv) Impact of the Coverage through $d_0$ Choice. Detection performance is here evaluated for all schemes for unified coverage varying from 20 m to 50 m. Figure 15 depicts the obtained results for (a) PCMD approach and (b) PCMSn approach in terms of NMSE$_t$ and NMSE$_p$. Except for the w.o.PC scheme, for which a higher coverage is beneficial since transmitted power is higher (refer to (41)), for all PC schemes, $d_0$ increase leads to performance loss. Indeed, for higher $d_0$, the number of rings for which PC leads to transmission power decrease with respect to w.o.PC (for which $L^{s_c}(i,j)/d_0 < 1$) will be more important which affects the detection performance. This figure shows the interest of the proposed PC schemes for all coverage values when considering PCMD and for low coverage when considering PCMSn.
Figure 15: Performance evaluation versus coverage $d_0$ for different proposed PC schemes.
6. Conclusion

In this paper, we investigated the problem of rare events detection in Wireless Sensor Networks (WSN) using the Compressed Sensing (CS) theory. In this context, two contributions are proposed. We first provided a theoretical, detailed formulation and proved the validity of the problem of CS based targets detection and counting. Then, we proposed a collaborative scheme which controls the transmitted power of some events in order to reduce the coherence of the sensing matrix thus guaranteeing an enhancement of CS recovery performance in WSN. Accounting for practical issues including sensors range and maximal allowed transmit power, we suggested two new schemes for power control that partition the sensor nodes into disjoint sets or clusters, respectively, based on the range of sensors from the cluster head "PCMD" and the deployed sensors density around the cluster head "PCMSn." Each of the two schemes of power control envisages either a local or a global distance effect compensation, which are, respectively, denoted as PCMDl and PCMDg for PCMD mechanism, and PCMSnl and PCMSng for PCMSn approach. Simulation results validate their superiority over the case without power control in terms of coherence reduction and reconstruction (detection and counting) performance. Under equal consumed power constraint, the global approach (for both distance and nodes number based schemes) outperforms the local approach characterized by its lower sensitivity to the partition granularity.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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