GENERALIZED TARGETS DETECTION AND COUNTING IN DENSE WIRELESS SENSORS NETWORKS

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ABSTRACT

This paper applies the Compressed Sensing (CS) the targets detection in small scale dense Wireless Sensors Networks (WSN). The monitored area is partitioned into cells, each equipped by one sensor. The CS application aims to locate targets from a reduced subset of sensors measurements. A generalized version of a recently proposed Greedy Matching Pursuit algorithm (GMP), designed for point events joint detection and counting, is derived, which is denoted by gGMP. This generalization enables the identification of several active cells at each iteration. Also, an optimized deterministic sensors subset selection scheme, based on the maximum energy is envisaged and shown to outperform the random choice scheme.

Index Terms— Dense Wireless Sensors Networks, rare targets detection, Compressed Sensing.

1. INTRODUCTION

Over the past few years, a new theory called Compressed Sensing (CS) emerged where a signal can be sampled and compressed simultaneously at greatly reduced rates. Then, the signal can be reconstructed from a small set of measurements if it is sparse in certain domain [1] [2]. Very recently interesting applications in wireless communication and networking [3] [4] based on CS theory are being envisaged. In particular, CS is adopted for events detection in Wireless Sensors Networks (WSN) [5] thus offering a great potential for energy consumption reduction thanks to the small number of required sensor measurements.

CS application in WSN is indeed based on the sparse nature of events to be detected, within the monitored area. As already considered in several works such as [6], the sparse events detection in WSN is studied under binary detection model using bayesian approach where each active detected cell contains at most one event. The events number counting in a monitored area which is investigated in [7] is of broad interest to many WSN applications such as intrusion detection and mobile object tracking [8] [10].

The sensors deployment over the monitored area depends mainly on the envisaged application. In a large scale WSN, a vast number of distributed sensor nodes are deployed over a large region. Such WSN are adequate especially in military fields for enemy and arms detection, in animals tracking in large forests, etc. In dense WSN, the density of sensors nodes is generally high over the monitored small area. In this scenario, the distance between neighboring nodes is small which is the case of industrial process monitoring like manufacturing broken down robots localization [11], intrusion detection and localization in commercial markets [8] and machine health monitoring [9].

In this work, we consider the location detection of spatially clustered targets through their transmitted signal detection. To this aim, the monitored area is partitioned into cells, each equipped by one sensor. The dense deployment of sensors makes that only a reduced fraction of them holds targets. As a consequence, the event of 'active cell' (cell with targets) is rare throughout the network thus giving an adequate framework for CS theory application. In particular, adapted Matching Pursuit (MP) approach is here applied for joint targets detection and counting. The paper contribution is a generalized extension of the recent Greedy Matching Pursuit (GMP) algorithm [7] denoted by gGMP. This generalization is based on the identification of more than one active cell position at each iteration. A similar generalization is studied in [12] in the case of the Orthogonal MP (OMP) for continuous entries sparse vector reconstruction in the noiseless case. On the contrary, in the context of discrete events detection and counting in dense WSN, the sparse parameter has discrete entries. The generalized algorithm gGMP acts for multiple active cells detection in the same iteration whereas in GMP [7], one active cell is detected at each iteration. Also, we propose a new deterministic sensors selection scheme based on global observation energy maximization.

The paper is organized as follows. The next section formulates the CS application in the WSN context. Section 3 emphasizes the two proposed contributions. First, the proposed gGMP algorithm is detailed. Second, the proposed scheme of sensors positions selection is presented. Finally, performance is evaluated in section 4 before the conclusion.

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2. PROBLEM FORMULATION

We consider a dense wireless sensors network deployed to locate potential targets presence. The monitored area is partitioned into N cells, each is equipped by one sensor. Some targets may be present and generate signals. In our work, like in [7] more than one target can be present per cell. Also, the targets are supposed spatially clustered which leads to a rareness of cells holding targets. Then, only a small fraction K among the N cells contain some events. Denoting by $\mathbf{s}$ the $K-$sparse vector giving the events number per cell, $\mathbf{s}_i$ its i^{th} component verifies $\mathbf{s}_i \in \{0, 1, \ldots, m\}$ where m is an integer representing an upper bound on the possible number of targets a cell can hold. In our study, a Time Division Multiple Access (TDMA) is adopted. In fact, during each time slot one sensor listens and reports its energy measurements to the fusion center thus avoiding any interference between sensors readings sending.

As mentioned above, we are interested with dense WSN where the spacing between two adjacent sensors is very small in such a way that the large scale fading effect can be neglected. Then, the received signal at sensor j corrupted by a complex Gaussian noise $\check{\mathbf{n}} \sim \mathcal{CN}\left(\mathbf{0}, \sigma^2\mathbf{I_N}\right)$ is expressed as

$$\mathbf{x}_j = \sum_{i\in\mathcal{E}} \mathbf{c}_{ij}\check{\mathbf{g}}_i + \check{\mathbf{n}}_j, \tag{1}$$

where $\mathcal{E}$ denotes the set of the active cells in monitored area. $\mathbf{c}_{ij} = \left[h_{i_1 j}, \ldots, h_{i_{\mathbf{s}_i} j}\right]$ gives the channels to sensor j of the $\mathbf{s}_i$ events in cell i where $h_{i_l j}$ captures the Rayleigh of the l^{th} target signal. $\check{\mathbf{g}}_i = [g_{i_1}, \ldots, g_{i_{\mathbf{s}_i}}]^T$ denotes the transmitted signal by the $\mathbf{s}_i$ events in cell i. The so generated signal g_{i_l} is modeled as $\sim \mathcal{CN}\left(0, P_0\right)$ where P_0 is the target transmitted energy. Concatenating $\mathbf{x}_j$ for $j = 1, \ldots, N$, leads to the N elements vector

$$\mathbf{x} = \mathbf{C}\check{\mathbf{g}} + \check{\mathbf{n}}, \tag{2}$$

where $\mathbf{C}$ is an $N \times \sum_{i=1}^{N} \mathbf{s}_i$ channel matrix, $\check{\mathbf{g}} = [\check{\mathbf{g}}_1^T, \ldots, \check{\mathbf{g}}_N^T]^T$ is the vector of targets transmitted signals.

The j^{th} sensor received energy $\check{\mathbf{x}}_j$ is expressed as

$$E(\mathbf{x}_j\mathbf{x}_j^*) = \sum_{n\in\mathcal{E}}\sum_{n'\in\mathcal{E}} E\left(\mathbf{c}_{nj}\check{\mathbf{g}}_n^T\check{\mathbf{g}}_{n'}^*\mathbf{c}_{n'j}^H\right) + E(\check{\mathbf{n}}_j\check{\mathbf{n}}_j^*). \tag{3}$$

We suppose that the signals transmitted by one cell targets or different cells targets are uncorrelated. Also, these signals are supposed uncorrelated with channels. Indeed, the last expression can be written as

$$E(\mathbf{x}_j\mathbf{x}_j^*) = \sum_{n\in\mathcal{E}} E\left(\sum_{l=1}^{\mathbf{s}_n} h_{n_l j} g_{n_l} \sum_{l'=1}^{\mathbf{s}_n} h_{n_{l'} j}^* g_{n_{l'}}^*\right) + E(\check{\mathbf{n}}_j\check{\mathbf{n}}_j^*),$$

$$= \sum_{n\in\mathcal{E}} E\left(\sum_{l=1}^{\mathbf{s}_n} |h_{n_l j}|^2 |g_{n_l}|^2\right) + \sigma^2. \tag{4}$$

In practice, the last energy expression is evaluated by averaging over samples during an interval over which a block fading channel is considered. Also, the Rayleigh fading channels between one cell targets and a given sensor are supposed to verify $h_{n_l j} = h_{nj}$ for $l = 1, \ldots, \mathbf{s}_n$. Then, the j^{th} sensor received energy can be approximately by

$$E(\mathbf{x}_j\mathbf{x}_j^*) = P_0 \sum_{n=1}^{N} |h_{nj}|^2 \mathbf{s}_n + \sigma^2, \tag{5}$$

$$= \sum_{n=1}^{N} \mathbf{\Phi}_{nj}\mathbf{s}_n + \sigma^2. \tag{6}$$

Concatenating the N sensors energy measurements, we obtain

$$\check{\mathbf{x}} = \mathbf{\Phi}\mathbf{s} + \eta, \tag{7}$$

where $\mathbf{\Phi}$ is $N \times N$ target decay energy matrix and $\eta = \sigma^2\mathbf{1}_N$. As most of cells do not hold targets, the CS theory can be applied to reconstruct the $K-$ sparse signal $\mathbf{s}$ from the recovered energy vector $\check{\mathbf{x}}$ using a subset of M measurements where $K < M \ll N$. Let $\mathbf{y}$ be a $M \times 1$ vector representing the M selected sensors energy measurements. Then, we have

$$\mathbf{y} = \mathbf{A}\mathbf{s} + \mathbf{n}, \tag{8}$$

where $\mathbf{A}$ is $M \times N$ submatrix of $\mathbf{\Phi}$ and $\mathbf{n} = \sigma^2\mathbf{1}_M$.

3. PROPOSED APPROACHES DESIGN

In this section, we will describe the proposed sparse targets detection and counting gGMP algorithm. After that, we will develop the proposed scheme for an optimal sensors positions selection.

3.1. Generalized Greedy Matching Pursuit algorithm

In our context, we exploit the rare nature of cells holding targets in the monitored area to apply CS approach for targets detection and counting. More precisely, we propose a novel Generalized Greedy Matching Pursuit (gGMP) algorithm based on multiple active cells detection at each iteration. Contrarily to [12] where the generalization is established in a noiseless scenario for the recovery of continuous entries sparse vector, the rare events number structure has discrete entries and the observation is contaminated by noise.

Otherwise, with the classical GMP algorithm [7], at each iteration only one cell is detected as active and the number of its targets is counted. With the proposed gGMP version, the targets detection and counting in $q > 1$ cells is processed at each iteration. The different steps of the new gGMP method are detailed hereafter.

At iteration i, we search the set $\mathcal{P}^{(i)}$ of possible combinations of q positions taken from $\Omega^{(i-1)}$ where $\Omega^{(i-1)}$ is the set of cells indices not still detected as active. Then, since each

active cell can hold a number of targets in $\{1, \dots m\}$, we form $\mathcal{V}$ as the set of vectors of q elements each taking their values from $\{1, \dots m\}$. Adding the vector of q all elements at zero to $\mathcal{V}$, its cardinal is $card(\mathcal{V}) = m^q + 1$.
The optimization step consists in finding the best element p in $\mathcal{P}^{(i)}$ (cells positions) associated to an element v in $\mathcal{V}$ (associated number of targets per cell) which most contributes to the residual observation $\mathbf{y}^{(i)}$. The result of iteration i is the $N \times 1$ vector $\mathbf{z}_{opt}^{(i)}$ which minimizes $\|\mathbf{y}^{(i)} - \mathbf{A}\mathbf{z}_p^v\|_2^2$ over possible $\mathbf{z}_p^v$ vectors with active (non zero) positions p in $\mathcal{P}^{(i)}$ and corresponding values v in $\mathcal{V}$. The so detected q cells have positions denoted by $p_{opt}^{(i)} \in \mathcal{P}^{(i)}$ and associated targets number $v_{opt}^{(i)} \in \mathcal{V}$.
$\Omega^{(i)}$ is then updated by subtracting the q newly detected positions. $\mathbf{y}^{(i)}$ is updated by subtracting the located events contribution from the residual observation according to (11) where $\mathbf{A}^{(i)}$ is the submatrix of $\mathbf{A}$ containing columns with positions $p_{opt}^{(i)}$.

- *Input:*
  An $M \times N$ measurement matrix $\mathbf{A}$.
  An $M-$ dimensional signal measurement vector $\mathbf{y}$.
  An q detected cells number at each iteration.
- *Output:*
  An $N-$ dimensional reconstructed signal $\hat{\mathbf{s}}$ with integer entries.
- *Procedure:*

Initialization: iteration count $i = 0$,
residual vector $\mathbf{y}^{(0)} = \mathbf{y}$,
$\Omega^{(0)} = \{1 \dots, N\}$ and $l^{(0)} = 0$.
reconstructed signal $\hat{\mathbf{s}} = \mathbf{0}_{N \times 1}$.
Iteration:
while $l^{(i)} = 0$ **do**
$i = i + 1$
1) Form the sets $\mathcal{P}^{(i)}$ and $\mathcal{V}$.

$$p_{opt}^{(i)}, v_{opt}^{(i)} = arg \min_{p \in \mathcal{P}^{(i)}, v \in \mathcal{V}} \|\mathbf{y}^{(i-1)} - \mathbf{A}\mathbf{z}_p^v\|_2^2 \qquad (9)$$

$$l^{(i)} = Card\left(\{j \backslash v_{opt}^{(i)}(j) = 0, \text{ for } j = 1, \dots, q\}\right).$$

2) Updating phase

$$\Omega^{(i)} = \Omega^{(i-1)} \backslash \{p_{opt}^{(i)}\} \qquad (10)$$

$$\mathbf{y}^{(i)} = \mathbf{y}^{(i-1)} - \mathbf{A}^{(i)} v_{opt}^{(i)} \qquad (11)$$

$$\hat{\mathbf{s}}(p_{opt}^{(i)}) = v_{opt}^{(i)} \qquad (12)$$

end while
return $\hat{\mathbf{s}}$

3.2. Sensors Positions Selection Scheme

We here propose an optimized sensors positions selection scheme in the aim of enhancing the detection performance compared to random selection as used in [7]. Indeed, only a reduced number of M measurements are needed for s reconstruction such that $M \ll N$. In this way, M sensors should be activated at a time while the remainning can enter sleep mode, which may extend the network life duration. We here adopt an optimized choice in the sense of selecting the highest measured energy sensors among the N sensors.

4. NUMERICAL RESULTS AND ANALYSIS

4.1. Simulation Parameters

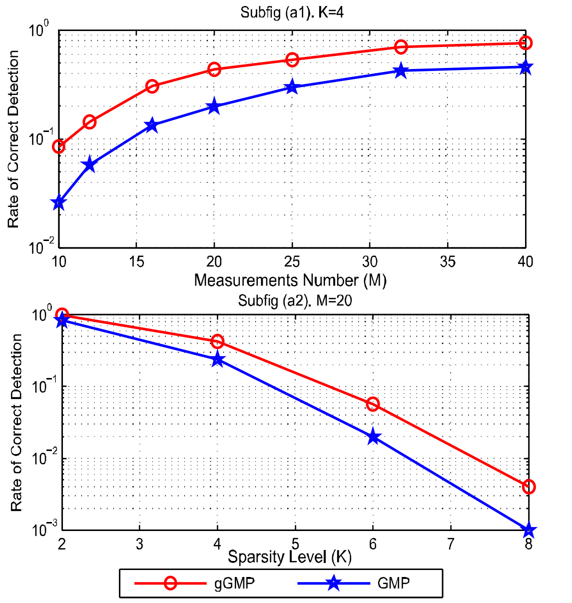
For simulation parameters, we consider a small regular monitored area with $16m \times 16m$ divided into $N = 64$ cells (8 by 8 cells), each cell is equipped with one sensor. Then, the distances between any two neighboring nodes are fixed to $2m$ which leads to a small and dense monitored area with almost $20m$ as higher remoteness between sensors. We activate sensors in $M = 20$ cells. Among the N cells, we select randomly $K \ll M$ active cells where the targets number is chosen uniformly at random from $\{1, 2, 3\}$ ($m = 3$). The target transmitted power is fixed to $P_0 = 1$. For the generalized version, the case of two cells detection at each iteration ($q = 2$) is envisaged.
The performance is evaluated in terms of experimental evaluation of Normalized Mean Squares Error (NMSE$_t$) on s and on active cells wrong detection (independently from the estimated number of events) (NMSE$_p$), accounting for both missing and false alarm. Their expressions are respectively given by

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

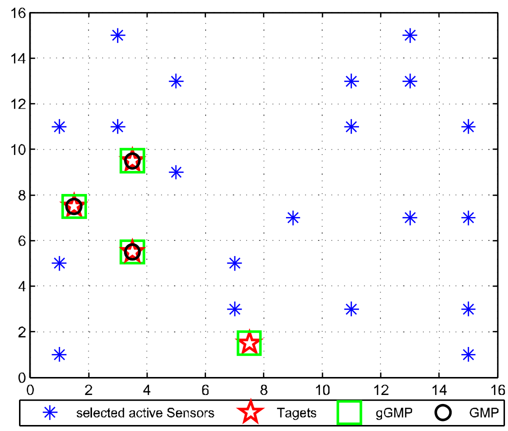
where s and $\hat{\mathbf{s}}$ denote the true and estimated vectors of events number per cell, $\mathbf{z}$ and $\hat{\mathbf{z}}$ are binary vectors obtained respectively from s and $\hat{\mathbf{s}}$ by placing 1 at non zero valued entries positions and 0 elsewhere. Additionally, the rates of correct detection and counting error over the true detection realizations are reported.

4.2. Numerical Results

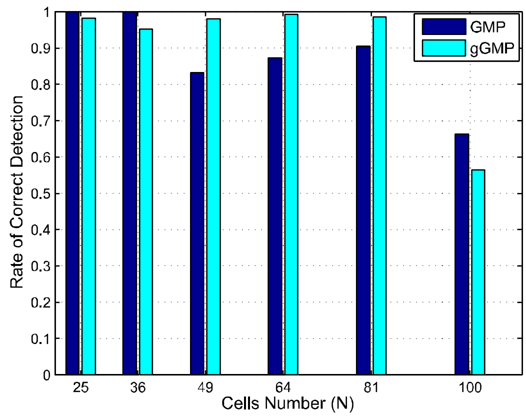
We first study the performance of GMP and the proposed gGMP versus the number of measurements M and the sparsity level K for $N = 64$ and SNR= 20dB. Figure (a) displays the rate of correct position detection. Subfig. $(a1)$ is obtained for $K = 4$ and varying M and subfig. $(a2)$ for $M = 20$ and varying K. It is noticed that the larger M is, the bigger is the rate of correct cell positions detection. It can be observed that gGMP achieves better detection rate than GMP version. Simularly, gGMP acheives an enhaced best detection rate compared to GMP. Also, for fixed M, better detection performance is obtained for lower K. Figure (b) illustrates an example of targets localization where we select randomly



(a) Comparison of gGMP and GMP when SNR=20dB.



(b) Targets positions estimation when SNR= 10dB when $N = 64$, $K = 4$, $M = 20$ and $q = 2$.



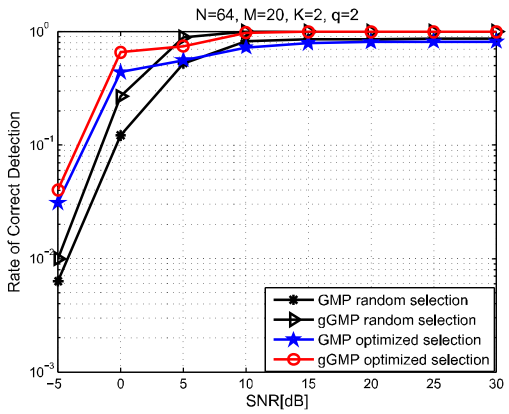
(c) Correct events position detection versus cells number when $M/N \approx 0.3$, $K/N \approx 0.03$, $q = 2$ and SNR= 20dB.

$M = 20$ sensors and fix SNR= 10dB. This example clearly indicates that gGMP can precisly recover the $K = 4$ targets locations whereas GMP correctly estimates the locations of all but one target. For the sensors density effect analysis, figure (c) reports the rate of correct detection versus the number of the square network cells number N ranging from 25 to 100. We also set the compression and the sparsity levels almost constant at respectively $M/N \approx 0.3$ and $K/N \approx 0.03$. As N increases the detection rates remain very good even if a slight decrease is observed for larger N as it also implies larger K. Also, we can see that gGMP has in average a better detection rate.

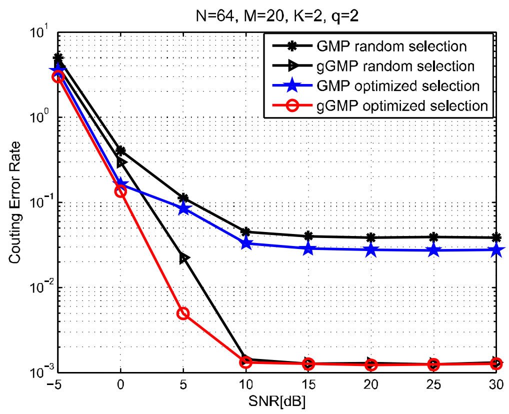
We now consider the comparison of the proposed sensors selection scheme to the random selection strategy. Then, the rate of correct detection curves versus SNR obtained by GMP and gGMP algorithms are displayed in figure (d) and demonstrate an improved performance of the proposed optimized scheme over the random selection mainly at low SNR values. From 10dB, the two compared schemes exhibit similar behavior. Also, the two proposed schems, combination of gGMP algorithm and optimized sensors selection mode acheive the lowest rate of counting error at low SNR as shown in figure (e). NMSE$_t$ curves obtained by different considered approaches are superimposed in figure (f). We can observe an enhanced performance of gGMP algorithm compared to GMP version over the whole SNR range. In addition, a sligh improvement of recovery accuracy of the proposed optimized selection mode is obtained especially at low SNR. Almost a similar behavior of NMSE$_p$ performance is observed in figure (g), which depicts the mean error on cell positions detection.

5. CONCLUSION

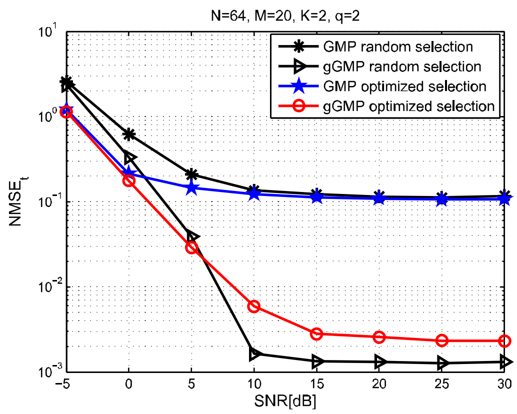
This paper investigated the problem of targets detection and counting in small scale wireless sensors networks from the perspective of compressive sensing theory application. We first proposed a new generalized extension of the recent Greedy Matching Pursuit (GMP) algorithm called Generalized GMP (gGMP) for sparse targets recovery. Our approach allows to identify simultaneously multiple active cells positions and their events number at each iteration. Simulation results validate the superiority of the proposed gGMP over the existing GMP algorithm in terms of correct cell position detection and mean squares errors. Further, we considered the problem of optimized sensors placement for which we proposed a new scheme based on measured observation energy maximization. The proposed optimal sensors selection realizes an enhancement of detection capacity and counting error reduction compared to the random sensors selection especially at low SNR.



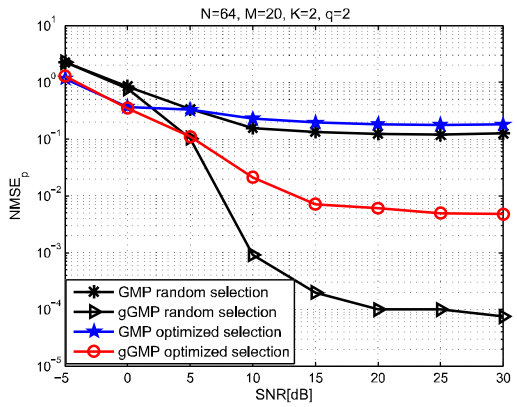
(d) Rate of correct detection versus SNR.



(e) Counting error versus SNR.



(f) Normalized MSE (NMSE$_t$) versus SNR.



(g) NMSE on cell positions detection versus SNR.

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