Cooperative Game Approach for Mobile Primary User Localization Based on Compressive Sensing in Multi-antenna Cognitive Sensor Networks

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Abstract

In this paper, the problem of joint energy efficient spectrum sensing and determining the mobile primary user location is proposed based on compressive sensing in cognitive sensor networks. By utilizing compressive sensing, the ratio of measurements for the sensing nodes are considerably reduced. Therefore, energy consumption is improved significantly in spectrum sensing. The multi-antenna sensors is also considered to save more energy. On the other hand, multi-antenna sensor utilization is a proper solution instead of applying more sensors. The problem is formulated to maximize the network lifetime and find the mobile primary user position by sensors selection under the detection performance and accuracy of localization constraints. For this purpose, a cooperative game is proposed to study this problem. It is shown that with the proposed game, the network lifetime is maximized while the proper sensors which participate in spectrum sensing and primary user localization are determined. Simulation results show that the network lifetime is improved while the detection performance constraint is satisfied and the location of the primary user is determined with high accuracy.

Keywords: Cooperative Spectrum Sensing; Compressive Sensing; Mobile Primary User Localization; Detection Performance; Game Theory.

1- Introduction

Recently, cognitive radio (CR) has a lot of attention due to its capability of exploiting white spectrums and improving spectral utilization efficiency [1], [2]. This capability is introduced as spectrum sensing which is a technique for determining the existence of the primary users (PUs). However, in an unauthentic network, malicious users (MUs) may imitate the features of PUs and transmit in the cognitive sensing band by reconfiguring the air interface of CR. These are introduced as primary user emulation attacks (PUEA) [3]. According to this, cognitive radio users mistake the adversary of CRs as primary users. Therefore, this will lead to wastage of spectrum resources and interference to the spectrum management of cognitive radio networks. In this case, information about PUs location could enable several capabilities in cognitive radio networks, including improved spatio-temporal sensing, intelligent location-aware routing, as well as aiding spectrum policy enforcement [4]. In order to obtain the primary user position in cognitive radio networks (CRNs), CRNs can be considered as wireless sensor networks (WSNs) [5]. Therefore, the sensors sense the spectrum band in WSN. However, the limited energy budget and low computational capability of each node are the main constraints of WSNs. Although, the sensor nodes have these constraints, the fusion center (FC) usually has a comparatively high computational capability. In fact, the sensors sense the spectrum band and transmit their results to FC. Then, FC makes a final decision about the channel status using a fusion rule. The fusion rules can be the hard decision rules such as OR, AND or K-out-of-N or soft decision rules such as Maximum Ratio Combining (MRC) for combining the local reports from different sensors.

Due to the limitations of the sensors capabilities, compressive sensing (CS) was introduced. Compressive sensing has a surprising property in which sparse signals can be recovered from far fewer samples than the Nyquist-shannon sampling theorem [6]. In fact, compressing sensing technology can be considered as an important method for spectrum sensing since wireless signals in these networks are typically sparse in frequency domain [7]. CS theory states that a signal can be reconstructed from a smaller number of linear measurements if it is sparse or compressible in a certain basis. Therefore, the conventional and compressing sensing techniques can be compared to illustrate that CS improves the energy efficiency and also the lifetime for cognitive sensor network [8]. In [9], the recent advances of compressive sensing in wireless sensor networks is stated. In this paper,

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CS can be efficiently applied to solve the problems specific to WSNs.

In [10], an energy-efficient spectrum sensing scheme is proposed based on game theory for cognitive radio sensor networks to prolong the network lifetime. However, there is not any mathematic analysis and simulation results to show the lifetime improvement in these networks. In [11], the problem of energy efficient cooperative spectrum sensing in multi-antenna cognitive sensor networks is investigated by sensing nodes selection while maintains the detection performance constraints. In [12], received-signal strength (RSS) method is used to estimate the PU position. In [13], primary user localization is also considered by utilization of the received-signal strength (RSS) and direction-of-arrival (DoA) estimation from sectorized antenna. In this case, a sectorized antenna is defined as an antenna that is set to different operating modes which leads to the selection of the signals that arrive from within a certain range of angles. In [14], a sparse vector is obtained by formulating the spectrum sensing and primary user localization problem. The CS technology is applied to reconstruct the information of the primary users. In [15] a decentralized way is proposed to solve the spectrum sensing and primary user tracking problem. However, existing works often investigate the CR network with static primary users and network lifetime improvement is not considered in these papers. In [16], the compressed sensing approach is proposed to overcome hardware limitations and acquire the measurements of the signals at the Nyquist rate when the spectrum is large. In [17], a data gathering algorithm is designed to do compressive sensing and select sensors in temporal and spatial domains, respectively. In [18], a cooperative support identification scheme is proposed for recovery of the compressive sparse signal via resource-constrained wireless sensor networks.

In [19], the authors apply a primary user localization algorithm based on compressive sensing in cognitive radio networks. They use the correlation coefficients between primary signal and secondary users (SUs) to estimate the primary user position. However, they do not consider the lifetime improvement in their work.

Summarily the contributions in this paper are as follows

- The problem is the lifetime maximization of cooperative spectrum sensing in wireless cognitive sensor networks by proper selection of the sensors for spectrum sensing and mobile primary user localization under the constraints on the false alarm and detection probabilities and accuracy of the mobile primary user localization. In this case, the distances between each node and FC are assumed to be known.
- An approach is also used based on compressive sensing (CS) framework to monitor the primary user localization and reduce the number of required samples to reconstruct the sampled signal at the fusion center (FC) and so decrease the energy consumption of the sensors. To save more energy, the multi-antenna structure is considered for each sensor and MRC is utilized as the diversity technique for antenna's signal combination. Therefore, the network lifetime is improved significantly.
- The optimum solution for the problem is the exhaustive search algorithm. This method cannot be used in practice due to its high computational complexity. Hence, a cooperative game is proposed to maximize the lifetime of the network and find the location of the mobile primary user with high accuracy.
- The numerical results analyze the proposed algorithm to find the solution, energy consumption, detection performance and accuracy of mobile primary user localization in different conditions.

The rest of the paper is organized as follows. The system model of a wireless sensor network is introduced in section 2. The problem is formulated in Section 3. In Section 4, the iterative algorithm is proposed. In section 5, the performance evaluation is stated and conclusions are finally drawn in Section 6.

2- System Model

A grid network is considered involving one primary user, Msensor nodes and one fusion center (FC). Each sensor or primary user locates at the center of one certain gird. It is assumed that each primary user moves in each frame duration as denoted by T. On the other hand, in each frame duration, primary user stays on a new position. Fig.1 shows the spectrum sensing model in a wireless cognitive sensor network. During the sensing time, each node which participates in spectrum sensing, applies the energy detection to detect the primary user existence. Then, each sensor sends its result to the fusion center to make a final decision about the channel state. In fact, cooperative spectrum sensing is used as a solution to alleviate the fading and shadowing effects in wireless channels [20]. In order to determine the PU activity, each observation sample $X_j[k]$, has the data model as

$$H_1: \quad X_j[k] = s_j[k] + u_j[k] \tag{1}$$

$$H_0: \quad X_j[k] = u_j[k] \tag{2}$$

Where, $s_j[k]$ is the received primary user signal at the jth node while $u_j[k]$ is a Gaussian noise with zero mean and variance,σ_u^2.

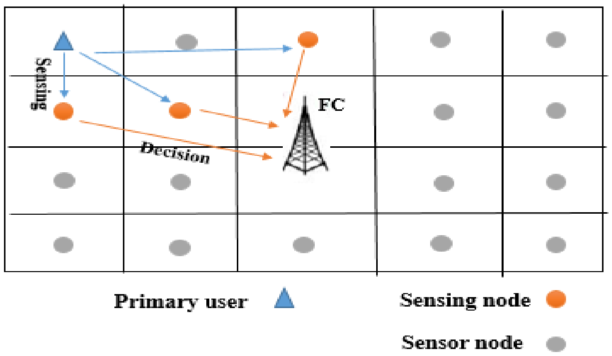

Fig.1 Cooperative spectrum sensing structure using the sensor nodes.

In spectrum sensing, the probability of detection states the protection probability of the primary user transmission from the interference made by the secondary user transmission while the probability of false alarm shows the opportunity of utilizing the idle band by the secondary users. The probability of false alarm in the jth cognitive sensor is given by using the energy detector method as follows [21]

$$P_{f_j} = Q\left(\left(\frac{\epsilon}{\sigma_u^2} - 1\right)\sqrt{\delta f_s}\right) \qquad (3)$$

Where, Q is the complementary distribution function of the standard Gaussian, ϵ is the detection threshold, δ is the sensing time and f_s is the sampling frequency. Also, under the hypothesis H_1 , the probability of detection for the jth cognitive sensor is stated by [21]

$$P_{d_j} = Q\left(\left(\frac{\epsilon}{\sigma_u^2} - \gamma_j - 1\right)\sqrt{\frac{\delta f_s}{2\gamma_j+1}}\right) \qquad (4)$$

Where γ_j is the received primary user signal to noise ratio at the jth cognitive sensor. Although, increasing the number of sensors helps to have more options for sensing nodes selection and therefore, it improves the detection performance. However, in recent years, multi-antenna utilization leads to decrease the cost of implementation. In fact, the soft decision strategy is utilized for signals combination of the antennas in each sensor. We apply MRC as a combination scheme. The distances between antennas are also considered more than half of the wavelength. In MRC, the effective SNRs for combined signals is defined as [11]

$$\gamma_{j,MRC} = \frac{P_t(\sum_{l=1}^{L}|h_{j,l}|^2)^2}{\sigma_{MRC}^2} \qquad (5)$$

Where, $h_{j,l}$is the channel gain between the lth antenna of the jth node and primary user and P_t is the transmitted power from the primary user. Variances of the effective noise can also be computed as

$$\sigma_{MRC}^2 = \sum_{l=1}^{L} |h_{j,l}|^2 \sigma_u^2 \qquad (6)$$

It should be noted that L is the number of antennas in each node. Therefore, the local probabilities of detection and false alarm are obtained by replacing Eq. (5) and Eq.(6) instead of γ_j and σ_u^2 in Eq.(3) and Eq.(4), respectively. However, fading and shadowing effects alleviate the detection performance. Hence, cooperative spectrum sensing is proposed to solve this problem. It means that each sensor sends its decision on the primary user existence to FC to make a final decision about the channel status using a combinational rule. In this paper, OR rule is considered as a combinational rule. It means that if at least one node reports that the spectrum band is busy, the final decision is the primary user activity. According to this definition, the global probabilities of detection and false alarm are obtained as

$$Q_f = 1 - \prod_{j=1}^{M}(1 - P_{f_j}) \qquad (7)$$

$$Q_d = 1 - \prod_{j=1}^{M}(1 - P_{d_j}) \qquad (8)$$

However, in [22], it is shown that participating all nodes in spectrum sensing is not necessary to improve the detection performance. Therefore, probability of participating in spectrum sensing is an important issue for each sensor. So, Eq.(7) and Eq.(8) are modified as follows

$$Q_f = 1 - \prod_{j=1}^{M}(1 - f_i P_{f_j}) \qquad (9)$$

$$Q_d = 1 - \prod_{j=1}^{M}(1 - f_i P_{d_j}) \qquad (10)$$

Where, f_i is the sensing probability, while $f_i \in [0,1]$. However, in an untrusted environment, spectrum sensing in cognitive radio networks not only requires to detect the signal in the spectrum band, but also it should confirm that whether the signal is from legal primary users or malicious users. Therefore, in this paper, the purpose is to find the location of the mobile primary user with high accuracy by selection of the appropriate sensing nodes so that the network lifetime is maximized and the detection performance constraints are satisfied. On the other hand, compressive sensing is introduced into the primary user localization to decrease the number of sensing sensors. In this case, the energy consumption is reduced and therefore the network lifetime is improved. It should be noted that the average energy consumption in spectrum sensing has two parts: the energy consumption for sensing the channel which is assumed to be the same for all sensors and it is denoted by E_s. The second part is the energy consumption for transmission of the sensing results to FC which is denoted by E_{t_j}. Since the transmission energy has an important effect on the battery lifetime, it cannot be ignored. The energy model in [22] is applied for the radio hardware energy dissipation as follows

$$E_{\mathrm{tj}}(d_j) = E_{t-elec} + e_{amp}{d_j}^2 \quad (11)$$

The first item presents the transmitter electronics energy, while the second part presents the energy consumption for amplifying the radio. d_j is the distance between the jth sensor and FC. Therefore, the total energy consumption for cooperative spectrum sensing is states as

$$E_T = \sum_{j=1}^{M}(E_s + E_{\mathrm{tj}}) \quad (12)$$

The area which nodes and primary user are distributed, is divided into N girds of the same size. Every node or primary user locates at the center of one certain gird. The received signal energy at grid i from primary user at grid j is considered using the Rayleigh energy decay model in [23] as follows

$$R_{i,j} = \frac{P_0 h_{i,j}}{{d_{i,j}}^2} \quad (13)$$

Where, P_0 is the power density at primary user. The location of the primary user is denoted by a vector $P_{N\times 1}$. Each element of the vector is zero except the grid which the primary user exists. The value of this element is P_0. It means that P is sparse. In order to localize the primary user, the conventional method is to place the sensor nodes at the monitored environment and obtain the snapshots of RSS. Thus, the received RSS,X, is a $N \times 1$ vector as[19]

$$X = \Psi \mathrm{P} \quad (14)$$

Where, Ψ is a $N \times N$ matrix represent the primary user energy decay model which is defined as

$$\Psi = \begin{bmatrix} \frac{h_{11}}{{d_{11}}^2} & \frac{h_{12}}{{d_{12}}^2} & \cdots & \frac{h_{1N}}{{d_{1N}}^2} \\ & & \cdots & \\ \frac{h_{N1}}{{d_{N1}}^2} & \frac{h_{N2}}{{d_{N2}}^2} & \cdots & \frac{h_{NN}}{{d_{NN}}^2} \end{bmatrix} \quad (15)$$

Using compressive RSS measurements instead of collecting all measurements, $Y_{M\times N}$ is defined which has the relationship to X. Therefore, we have

$$Y = \Phi X + W \quad (16)$$

Where,$\Phi_{M\times N}$ is the measurement matrix which $\Phi(i,j)$ represents the probability of sensing the channel by ith sensor in jth grid while W is the additive Gaussian white noise matrix. In order to reconstruct X which is K sparse (in this case, $K = 1$) in Ψ, Mcompressive measurements are required where $M = O(K \log N)$. For this reconstruction, a convex optimization problem should be solved which has the following form

$$\arg\min || P ||_{l_1} \quad , s.t. ||\Phi X - Y||_{l_2} < \epsilon \quad (17)$$

Where l_1 and l_2 are the corresponding norms in Eq. (17). This convex problem can be solved by linear programming and the global optimal solutions can be achieved.

3- Problem Formulation

As stated before, the problem is the selection of the sensors which determine the primary user existence and find its location, so that the network lifetime is maximized and the detection performance and accuracy of the primary user localization constraints are satisfied. For this purpose, the behavior of sensors is modeled as a cooperative game, in which, the ith sensor (ith player in the game) can determine its sensing probability. Therefore, the utility function of the ith node (lifetime of the ith node) is defined as

$$u_i = \frac{E_{R_i}}{E_{T_i}} \quad (18)$$

Where, E_{R_i} is the remaining energy after transmission of the result to FC and E_{T_i} is the energy consumption for the ith sensor. It should be noted that maximization of the utility u_i depends not only on f_i, the strategy taken by sensor i , but also on the strategy set of other sensors in the game. The strategy combination space of sensors in the game is considered as follows

$$F = \{f | f = (f_1, f_2, \dots, f_M), \forall i \in M, 0 \le f_i \le 1\} \quad (19)$$

On the other hand, each sensor for maximization of its utility function has to consider its strategy as well as the strategies taken by the other sensors. On the other hand, all players want to maximize the network lifetime (aggregate utility) while maintaining fairness. Hence, the aggregate utility is given by

$$U_L = \sum_{i=1}^{M} f_i\, u_i \quad (20)$$

As it is said, our goal is to maximize the aggregate utility in the system which is equal to maximize the network lifetime. It should be noted that in cooperative spectrum sensing, it is desirable to have higher global probability of detection to decrease the interference of the primary user transmission with the secondary users' activities and also lower global probability of false alarm to have more opportunity for spectrum utilization. According to this, the problem can be formulated as

$$P1:_{f_i} Max\ U_L \quad (21)$$

$$s.t. \quad Q_d \geq \beta \quad (21\text{-}1)$$

$$Q_f \leq \alpha \quad (21\text{-}2)$$

$$\sum_{i=1}^{M} {f_i}^2 \leq M \quad (21\text{-}3)$$

$$||\Phi X - Y||_{l_2} < \zeta \quad (21\text{-}4)$$

Eq. (21-1) and Eq.(21-2) show the detection performance constraints while Eq.(21-3) states the probability of participating in spectrum sensing for each sensor node . ζ in Eq.(21-4) is a threshold which shows the accuracy of mobile primary user localization using compressive sensing. The optimal solution for this problem is the exhaustive search method with high complexity with the order of $O(M!)$. Although, heuristic methods are alternative approaches, but they lead to the sub-optimal solutions. Thus, it is desirable to search a distributed approach with linear complexity and optimal solutions for cognitive sensor network. Therefore, the primary user localization (PUL) is modeled as a cooperative game which is defined as

Definition 1: A PUL game can be stated as (M, S, U) in which, M is the number of sensors (players), S is the set of strategies and U is the set of utility functions. Each sensor (player) i determines its strategy $s_i$and gets the utility (payoff)u_i. In fact, u_i is the function of strategy combination set $(f_1, f_2, \ldots, f_M)$.

In the game theoretic scenario, it is essential to obtain an equilibrium state for the game which is called Nash equilibrium (NE) [24]. A Nash equilibrium offers a stable solution in which the players achieve a point where no player wants to deviate. On the other hand, a Nash equilibrium states the best status for all players. It should be noted that the efficiency of NE is dependent on utility function of the players. From another respective, for achieving the global optimization, the utility function should be designed so that NE exists. The following conclusion shows the existence of Nash equilibrium in the primary user localization game.

Prposition1: A Nash equilibrium exists in the primary user localization (PUL) game.

Proof: We hope that when all sensors reach the NE, mobile primary user localization and network lifetime maximization are also obtained. To get the NE point, the Lagrangian function is applied as follows

$$L = \sum_{i=1}^{M} f_i\, u_i + \lambda(Q_d - \beta) - \eta\big(Q_f - \alpha\big) - \xi\big(\sum_{i=1}^{M} {f_i}^2 - M\ \big) - \vartheta(\big||\Phi X - Y|\big|_{l_2} - \zeta) \quad (22)$$

Where λ , η , ξ and γ are the Lagrangian multipliers. It should be noted that for each node, P_{f_j} is not dependent on SNR. On the other hand, all sensors have the same local probability of false alarm. It means that, the global probability of false alarm constraint determines the maximum number of sensing nodes as follows

$$n \leq \frac{\ln(1-\alpha)}{\ln(1-Q_f)} = M\_s \quad (23)$$

Where, M_s denotes the maximum number of sensing nodes. Therefore, in Eq. (22), the global probability of false alarm constraint is removed, while the maximum number of sensing nodes constraint is considered in sensor selection. Therefore, we have

$$\frac{\partial L}{\partial f_i} = u_i - 2f_i + \lambda P_{d_i} - 2f_i\xi - \vartheta \sum_{i=1}^{M}(f_i \frac{h_{ij}}{{d_{ij}}^2} - y(i,j)) \quad (24)$$

So, we have

$$f_i = \frac{u_i + \lambda P_{d_i} - \vartheta \sum_{i'=1 \neq i}^{M}(f_{i'} \frac{h_{i'j}}{{d_{i'j}}^2} - y(i',j))}{2\xi + \vartheta(\frac{h_{ij}}{{d_{ij}}^2} - y(i,j))} \quad (25)$$

According to Eq. (25), for any two sensors $i, j \in N$, if $u_i > u_j$, $P_{d_i} > P_{d_j}$ and $d_j < d_i$, then the condition $f_i > f_j$ is satisfied. Therefore, the sensor selection leads to the energy balancing between nodes and therefore, the Nash equilibrium is obtained. In a Nash equilibrium, optimal probability of spectrum sensing is achieved for each player. Due to the existence and uniqueness of the Nash equilibrium, an iterative algorithm is used to find the equilibrium. Therefore, the optimal network lifetime can be obtained by finding the optimal NE point of the game.

4- Proposed Iterative Algorithm for Solving the Problem

In iterative algorithm, the optimum value of λ and ϑ are obtained. At each iteration, first, the sensors with enough energy (i.e., $(E_{R_i} - E_{T_i} > 0)$) are candidates for spectrum sensing. Then, the probability of spectrum sensing (f_i) is calculated for each sensor. The nodes with higher probability of spectrum sensing are selected for spectrum sensing until the detection performance and accuracy of compressive sensing constraints are satisfied. Note that maximum number of sensing nodes is determined using the global probability of false alarm constraint. Then, λ and ϑ are updated according to the subgradient method. Therefore, we have [25]

$$\lambda^{k+1} = \lambda^k - \Gamma_1^k (Q_d - \beta) \quad (26)$$

And

$$\vartheta^{k+1} = \vartheta^k + \Gamma_2^k \, ||\Phi X - Y||_{l_2} \quad (27)$$

The step size used in the proposed algorithm is $\Gamma_i^k = \frac{w_i}{\sqrt{k}}$ $i = 1,2$, where $w_i \gg 1$. In each iteration, the total energy consumption is also calculated. This proposed algorithm ends when the convergence metric is satisfied. Then, according to the sensing players, the primary user position is obtained. In fact, in the proposed algorithm, using the optimal value of λ and ϑ, the proper nodes are selected for spectrum sensing and primary user localization. Therefore, the network lifetime and primary user position are determined. Pseudo code for Primary User Localization and Lifetime Maximization Algorithm (PULLM) is shown below.

Algorithm1: PULLM Algorithm

λ_{min}=0
λ_{max}=χ
$\vartheta_{max} = \upsilon$
$\vartheta_{min} = 0$
λ=λ_{max} (input)
$\vartheta = \vartheta_{max}$ (input)
Iteration= α(a big number)
ε_1= small parameter
ε_2= small parameter
While ($|\lambda^{k+1} - \lambda^k| > \varepsilon_1$ && $|\vartheta^{k+1} - \vartheta^k| > \varepsilon_2$)
number of sensing sensors(n)=0
Determine the nodes which have enough energy, the number of nodes is $count$
Compute f_i for each node according to Eq.(25)
$n = 0$
While (select n nodes with higher probability of spectrum sensing <min($count, M\_s$))
Compute Q_d
If $Q_d > \beta$, break , **End**
$n = n + 1$
End
Compute energy consumption according to Eq. (12)
Compute remaining energy for the sensing nodes
Compute the accuracy for mobile primary user localization
Update λ andγ according toEq. (26) and Eq.(27)
End
The network lifetime and the location of the primary user are obtained (outputs).

Fig.2 Pseudo code for the proposed algorithm

5- Performance Evaluation

To evaluate the performance of PULLM game approach, it is assumed that the reports are generated and transmitted per round. In each round, the primary user moves with uniform distribution in a square field with a length of 700 m. FC is located in the center of the environment and the number of nodes is changing from 5 to 50 in values. The nodes which their remaining energy is more than their energy consumption, are supposed to be alive. According to this, the lifetime definition is the time in which more than 25% of sensors are alive. The initial energy for each node is set to be 0.2 mJ. In simulation results, the design parameters are set as $\alpha = 0.1$ and $\beta = 0.9$. Every simulation result in this section is averaged over 10000 realizations.

We use 2.4 GHz IEEE 802.15.4/ZigBee as the communication technology for the cognitive sensor network. The simulation parameters are set in simulation table1 [23], [26].

Table1: Simulation parameters

Parameter	value
Maximum distance between two nodes	700m
Number of Nodes	5-50
Initial energy of the nodes	0.2mJ
E_s	190nJ
E_{t-elec}	80nJ
e_{amp}	$40.44 \mathrm{pJ/m^2}$

The proposed algorithm is compared with the following algorithms:

Network Lifetime Improvement with Sensor Selection (NLISS): In this algorithm, the sensors with more remaining energy, probability of detection and less energy consumption are selected for primary user localization. For lifetime maximization in this algorithm, the convex optimization method is used. In this case, the Lagrangian multipliers are updated using subgradient search method [26].

Random Sensor Selection for Network Lifetime (RSSNL): In this algorithm, the sensors are selected randomly for mobile primary user localization and spectrum sensing. This algorithm has the low complexity to solve the problem.

In Fig.3, the minimum remaining energy of the sensors is shown versus different number of nodes. According to Eq. (21), the algorithms attempt to balance the remaining energy of the nodes to maximize the network lifetime.

PULLM algorithm and PULLM algorithm have more minimum remaining energy. Because these algorithms consider local probability of detection, energy consumption, remaining energy and accuracy of primary user localization for sensors selection. RNLSS algorithm has low remaining energy due to the random selection of the sensing nodes. It should be noted that multi-antenna sensors help to balance the remaining energy between sensors. It is noted that the chance of sensor selection increases as the number of nodes is increased. It leads to have more minimum remaining energy in large number of nodes.

Fig.4 shows the energy consumption versus different number of sensors. PULLM using multi-antenna sensors algorithm consumes less energy because multi-antenna sensors are very effective for saving energy especially in large environments. Another important issue is the compressing sensing method which saves the energy consumption. NLISS algorithm consumes more energy than proposed algorithms. This shows that the proposed algorithms are energy efficient in spectrum sensing and primary user localization. It should be noted that the algorithms are compared when they satisfy the detection performance and the accuracy of mobile primary user localization constraints.

Fig.5 shows the successful percent of finding the solution for algorithms in different number of sensors. Howevere, sometimes the problem has no solution. It means that the constraints of the problem are not satisfied by selection of all alive sensors. According to Fig.5, if the problem has the solution, the proposed algorithm with multi-antenna sensors has the most success in finding the solution. NLISS algorithm has less success in finding the solution, because it is not considered the accuracy of the primary user localization in this algorithm. RSSNL algorithm has the minimum percent of success in finding the solution due to the random selection of the sensing nodes. According to this experiment, by increasing the number of nodes, in RSSNL algorithm, it is possible to select the nodes with lower probability of detection and therefore, this metric is decreased. It should be noted that this metric is very important to determine the efficient algorithm.

In Fig.6, the mean error of the network for different number of sensors is illustrated. In fact, this parameter shows the accuracy of the algorithms in mobile primary user localization. According to Fig.6, RSSNL algorithm has the maximum mean error due to the random selection of the nodes for primary user localization and spectrum sensing while the proposed algorithms have the minimum mean error. Because these algorithms consider the accuracy of primary user localization in sensing nodes selection. On the other hand, the sensors which are located near to the primary user have more opportunity for spectrum sensing. However, in NLISS algorithm, decreasing of the mean error of the primary user tracking is not considered for sensor selection.

Fig.7 and Fig.8 are the focused versions of Fig.6. It is obvious that the proposed algorithms have the least mean error in primary user localization due to considering this metric in sensing node selection while in NLISS algorithm, this metric is not important in sensor selection.

Fig.9 shows the utility function of the algorithms versus different number of nodes. According to Eq. (21), the purpose is to maximize the aggregate utility function. In fact, this parameter equals to the network lifetime and increasing of the aggregate utility function improves the network lifetime. It is illustrated that PULLM algorithm with multi-antenna has more utility function than PULLM algorithm. It means that the multi-antenna technique improves the lifetime of the network due to the selection of the sensors based on their energy consumption, remaining energy, global probability of detection and accuracy of primary user localization. It should be noted that by increasing the number of the sensors, the chance of the sensor selection also increases and therefore, the utility functions of the proposed algorithms are improved.

Fig.10 shows the changes of the utility function versus the iterations in which the Lagrangian multipliers are updated. The iterations are changed between 340 and 570. Number of nodes is set to 50. According to Fig.10, in 520th iteration, the utility function converges to the fixed value.

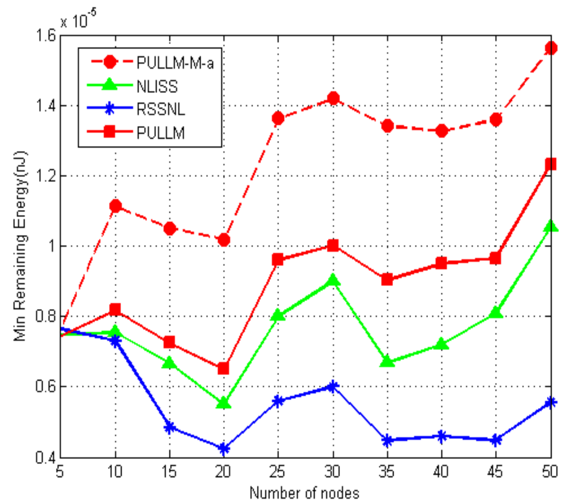

Fig.3 Minimum remaining energy vs. different number of nodes

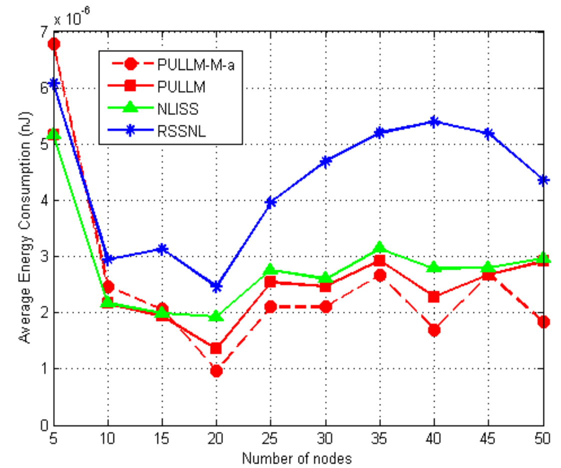

Fig.4. Average energy consumption vs. different number of nodes

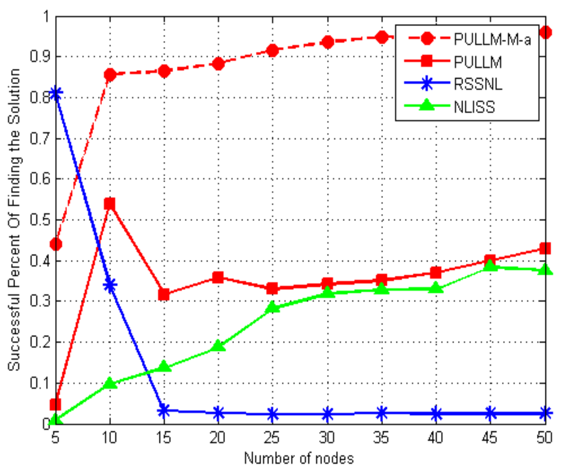

Fig.5 Successful percent of finding the solution vs. different number of nodes

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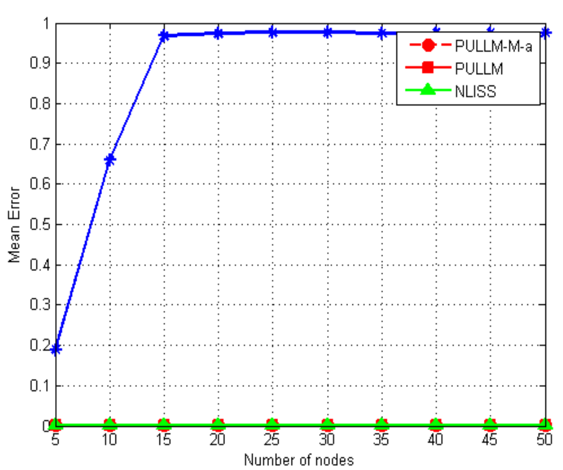

Fig.6 Mean error vs. different number of nodes

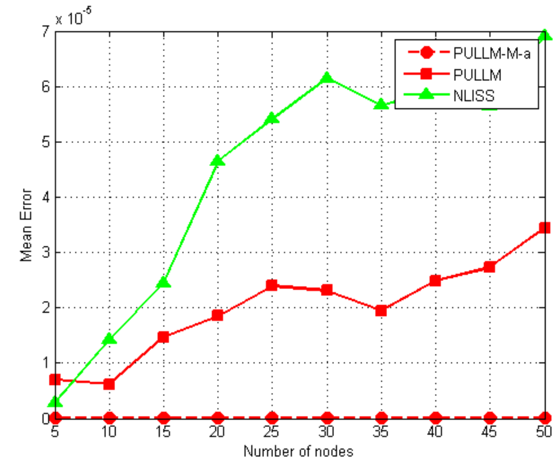

Fig.7 Mean error versus different number of nodes

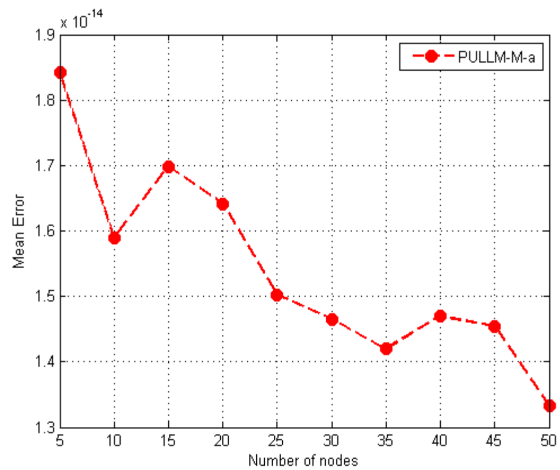

Fig.8 Mean error vs. different number of nodes

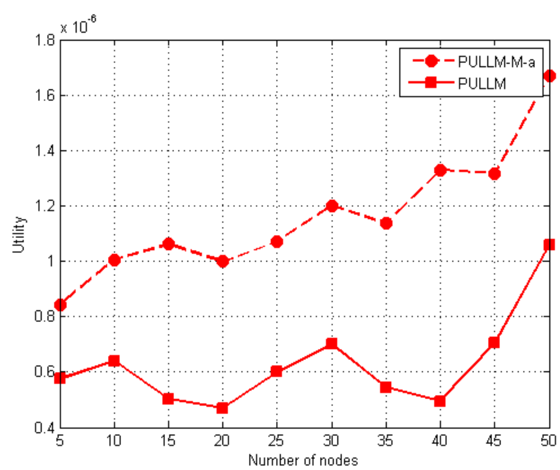

Fig.9 Utility function versus different number of nodes

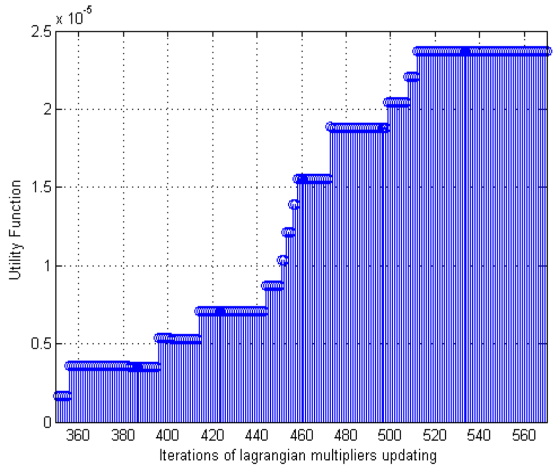

Fig.10. Utility function convergence for different iterations

6- Analysis on Results

In this paper, the purpose is the network lifetime maximization of cooperative spectrum sensing in wireless cognitive sensor networks by proper selection of the sensors for spectrum sensing and mobile primary user localization under the constraints on the false alarm and detection probabilities and accuracy of the mobile primary user localization. To save more energy of the sensors, compressive sensing (CS) framework and multi-antenna structure for each sensor are used to monitor the primary user localization.

Fig.3 and Fig.4 show the effectiveness of the proposed algorithms for improving the network lifetime. In fact, less energy consumption of the network and more remaining energy of the sensors increase the network lifetime. The proposed algorithms improve these parameters and therefore, maximize the network lifetime. Another important parameter is the successful percent of finding the solution which shows the ability of the algorithms in finding the solution. The proposed algorithms have the maximum percent in finding the solution. On the other hand, if the problem has the solution, the proposed algorithms have the most ability to find it. Fig.6, Fig.7 and Fig.8 show the mean error of the network for primary user localization. The proposed algorithms have the minimum mean error. Because these algorithms consider the accuracy of primary user localization in sensing nodes selection while RSSNL algorithm has the maximum mean error due to the random selection of the nodes for primary user localization and spectrum sensing. Fig.9 and Fig.10 show the utility function of the algorithms and changes of the utility function versus the iterations, respectively. In fact, utility function of each sensor is the ratio of its remaining energy to the energy consumption. Our purpose is to maximize the aggregate utility function. In fact, this parameter equals to the network lifetime and increasing of the aggregate utility function improves the network lifetime. According to this figure, the proposed algorithms have the maximum utility function.

7- Conclusion

Cooperative spectrum sensing has an essential role to mitigate the fading and shadowing effects in cognitive sensor networks. However, due to the limited energy budget of the sensors, the lifetime improvement should be considered in these networks.

In this work, the sensing nodes do spectrum sensing to determine the primary user activity and also track the mobile primary user location based on compressive sensing in cognitive sensor networks. This is a capability to detect the primary emulation attacks in cognitive radio networks. For saving more energy, the multi-antenna sensors is also considered. Therefore, the problem is formulated to maximize the lifetime of the network subject to the global detection performance and accuracy of the primary user localization. The problem is investigated using game theoretic solutions. Therefore, the primary user localization (PUL) is proposed as a cooperative game to solve the problem. It means that each node considers the utility function of itself as well as other sensors to improve the network lifetime and find the location of the mobile primary user with high accuracy. It is shown that the proposed algorithms maximize the network lifetime and satisfy the detection performance and accuracy of the mobile primary user localization constraints. In future, the capability of energy harvesting for sensors will be an essential issue for improving the lifetime of the cognitive sensor networks.

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