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Energy-efficient and Mobile-aided Cooperative Localization in Cognitive Radio Networks By Using Energy harvesting Method

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Abstract— **In cognitive radio networks (CRNs), primary users(PUs) localization is a key aspect to improve network performance in terms of reliability and power adaption. However, energy efficiency becomes a critical issue for localization in CRNs due to the limited energy storage in CR devices. In this paper we propose an Energy-Efficient Cooperative Localization Algorithm (EE-CLA) for PU positioning using a mobile-aided CR By using energy harvesting Method. Since cooperative communication among CRs is energy demanding, a mobile CR manager is introduced to balance the requirements for positional accuracy and power consumption restrictions by waking up only an appropriate number of CRs collaborating with the mobile CR manager. To investigate the influence of accurate location information, a location-aware CR (LaCR) routing protocol is also applied. Simulations are conducted to evaluate the performance of both proposed EE-CLA algorithm and LaCR protocol. Results confirm that the proposed EE-CLA outperforms its simplified version, named CLA algorithm, in terms of energy efficiency. Moreover, significant gains are obtained with the LaCR protocol in terms of CR end-to-end performance and PUs collision risk by using the localization information obtained from the EE-CLA algorithm.**

Index Terms—**cognitive radio networks, cooperative Localization algorithm , location-aware CR, Mobile CR manager.**

I. Introduction

The current inefficient spectrum usage calls for a new networking paradigm based on more flexible opportunistic utilization of the available spectrum. Cognitive Radio (CR) is envisaged as the key enabling solution to maximize the efficiency of spectrum usage. In Cognitive Radio Networks (CRNs), CR users are allowed to opportunistically use parts of the spectrum that are temporally unoccupied by the licensed Primary Users (PUs).

In most practical applications, knowledge of the PU position is fundamental to avoid harmful interference towards PUs, to implement a more efficient CR power adaptation, to handle mobility of CRs, and to design powerful location- ware routing protocols. A location-based CR routing protocol has been proposed to show the benefits of location information in CRNs. In fact, PU protection and CR routing performance improves using accurate location information.

Cooperative PU localization solutions have been proposed to reduce interference towards PUs under harsh channel conditions. In particular, cooperative communication among CRs leads higher detection sensitivity that overcomes the uncertainty within the channel, thus obtaining more precise estimation of the PU location. On the other hand, cooperative communication is energy-consuming, hence there is a trade-off between energy efficiency and localization accuracy in order to improve CRN performance. Also, CRs promise advanced functions (such as dynamic spectrum sensing), requiring advanced information processing capabilities that are energy demanding. Hence, CRs need powerful energy sources to support these functions, while in most practical situations the cognitive device is battery powered. As stated, an energy-constrained CR must utilize the available energy efficiently, and furthermore, under fading and multichannel conditions, tackle the problem of minimizing the energy consumption while optimizing spectrum sensing and access decisions. Therefore the energy efficiency for localization algorithm design exploiting the spectrum sensing information(e.g.,Received Signal Strength Indicator-RSSI measurements from energy detection–based spectrum sensing) is imperative, while it is not adequately addressed in CRNs literature.

Several works about energy management localization strategies have been already proposed in literature for wireless sensor networks (WSNs). However, the communication hypothesis for CRNs is different from the ones for WSNs, so WSNs solutions are not suitable for CRNs strategies. In particular, WSNs energy management solutions assume that data acquisition consumes significantly less energy than sensors transmission. Unfortunately, this assumption does not hold in a number of practical applications in CRNs. In fact, CR spectrum sensing functionality, which is partly equivalent to data acquisition in WSNs, is more energy demanding than CR transmission. Thus, energy efficient localization solutions for CRNs should also include the energy management of the sensing procedure. The existing energy efficient spectrum sensing protocols in CRNs apply sensor scheduling algorithm to optimally schedule the activities of the cognitive devices to provide the required sensing performance and increase the overall cognitive radio system throughput. Moreover, in CRNs non-cooperative PU behavior and its protection are the two main issues, which should be considered when designing the localization algorithms for CRNs. Generally speaking, experimental results have shown that the energy consumption of the CR devices in sleep mode is less than that in active (i.e., transmission) mode. As a result an important approach to reduce the power consumption is to switch the devices into the low-power sleep mode as much as possible.

In this paper, we propose an energy efficient cooperative localization algorithm (EE-CLA) using energy harvesting method that uses the RSSIs obtained from PUs through cooperative spectrum sensing. In order to estimate the PU position accurately, a mobile CR manager is introduced that collaborates with fixed CRs to balance the requirements of positional accuracy and power consumption restrictions.

Indeed, by using the mobile CR manager, only a limited number of CRs wakes up in a certain area defined local region. Based on the opportunistic wake up model, the mobile CR manager regulates the CRs' on-off states through changing the wakeup probability of each CR at different local regions. However, the proposed cooperative localization solution ensures that the number of active CRs is large enough to accurately locate the PU. The main characteristic of the proposed EE-CLA algorithm is that, by employing the mobile CR manager through an energy efficient cooperative algorithm, it provides a sensitive detector even in harsh channel conditions without leading to higher hardware complexity. From an implementation perspective, it leads to the reduced hardware cost and complexity. Furthermore, the proposed localization algorithm not only reduces communication overhead in a local region, but also improves the energy efficiency due to the wake up energy modeling in the data acquisition phase, while maintaining a good localization precision.

Finally, a location-aware CR routing protocol(LaCR) is implemented to show the benefits of location information in CRNs. LaCR routing algorithm exploits the existence of heterogeneous PUs and uses the position information obtained through EE-CLA algorithm to improve the CR power adaptation, CR end-to-end path length, and PU interference protection.

II. LITERATURE SURVEY

F. Akyildi et.al [1] Cognitive radio (CR) technology is envisaged to solve the problems in wireless networks resulting from the limited available spectrum and the inefficiency in the spectrum usage by exploiting the existing wireless spectrum opportunistically. CR networks, equipped with the intrinsic capabilities of the cognitive radio, will provide an ultimate spectrumaware communication paradigm in wireless communications. CR networks, however, impose unique challenges due to the high fluctuation in the available spectrum as well as diverse quality-of-service (QoS) requirements. Specifically, in cognitive radio ad hoc networks (CRAHNs), the distributed multi-hop architecture, the dynamic network topology, and the time and location varying spectrum availability are some of the key distinguishing factors. In this paper, intrinsic properties and current research challenges of the CRAHNs are presented. First, novel spectrum management functionalities such as spectrum sensing, spectrum sharing, and spectrum decision, and spectrum mobility are introduced from the viewpoint of a network requiring distributed coordination. A particular emphasis is given to distributed coordination between CR users through the establishment of a common control channel. Moreover, the influence of these functions on the performance of the upper layer protocols, such as the network layer, and transport layer protocols are investigated and open research issues in these areas are also outlined. Finally, a new direction called the commons model is explained, where CRAHN users may independently regulate their own operation based on pre-decided spectrum etiquette

H. Celebi [2] proposed Location awareness in cognitive radio networks .With the increasing advancements in the digital technology, future wireless systems are promising to support higher data rates, higher mobile speeds, and wider coverage areas, among other features. While further technological developments allow systems to support higher computational complexity, lower power consumption, and employ larger memory units, other resources remain limited. One such resource, which is of great importance to wireless systems, is the available spectrum for radio communications. To be able to support high data rate wireless applications, there is a need for larger bandwidths in the spectrum. Since the spectrum cannot be expanded, studies have been concerned with fully utilizing the available spectrum. One approach to achieve this goal is to reuse the available spectrum through space, time, frequency, and code multiplexing techniques. Another approach is to optimize the transceiver design as to achieve the highest throughput over the used spectrum. From the physical layer perspective, there is a need for a highly flexible and efficient modulation technique to carry the communication signal. A multicarrier modulation technique known as orthogonal frequency division multiplexing (OFDM) is one example of such a technique. OFDM has been used in a number of current wireless standards such as wireless fidelity (WiFi) and worldwide interoperability for microwave access (WiMAX) standards by the Institute of Electrical and Electronics Engineers (IEEE), and has been proposed for future 4G technologies such as the long term evolution (LTE) and LTE-advanced standards by the 3rd Generation Partnership Project (3GPP), and the wireless world initiative new radio (WINNER) standard by the Information society technologies (IST). This is due to OFDM's high spectral efficiency, resistance to narrow band interference, support for high data rates, adaptivity, and scalability. xiii In this dissertation, OFDM and multiuser OFDM , also known as orthogonal frequency division multiple access (OFDMA), techniques are investigated as a candidate for advanced wireless systems. Features and requirements of future applications are discussed in detail, and OFDM's ability to satisfy these requirements is investigated. We identify a number of challenges that when addressed can improve the performance and throughput of OFDM-based systems. The challenges are investigated over three stages. In the first stage, minimizing, or avoiding, the interference between multiple OFDMA users as well as adjacent systems is addressed. An efficient algorithm for OFDMA uplink synchronization that maintains the orthogonality between multiple users is proposed. For adjacent channel interference, a new spectrum shaping method is proposed that can reduce the out-of-band radiation of OFDM signals. Both methods increase the utilization of available spectrum and reduce interference between different users. In the second stage, the goal is to maximize the system throughput for a given available bandwidth. The OFDM system performance is considered under practical channel conditions, and the corresponding bit error rate (BER) expressions are derived. Based on these results, the optimum pilot insertion rate is investigated. In addition, a new pilot pattern that improves the system ability to estimate and equalize various radio frequency (RF) impairments is proposed. In the last stage, acquiring reliable measurements regarding the received signal is addressed. Error vector magnitude (EVM) is a common performance metric that is being used in many of today's standards and measurement devices. Inferring the signal-to-noise ratio (SNR) from EVM measurements has been investigated for either high SNR

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values or data-aided systems. We show that using current methods does not yield reliable estimates of the SNR under other conditions. Thus, we consider the relation between EVM and SNR for nondata-aided systems. We provide expressions that allow for accurate SNR estimation under various practical channel conditions.

R. Martin and R. Thomas [3]designed Algorithms and bounds for estimating location, directionality, and environmental parameters of primary spectrum users. Most existing work on dynamic spectrum access deals with creating a spectral and temporal map of spectrum white space, and then filling it. The spectrum can be better utilized by increasing the spatial awareness of secondary users to include knowledge of the locations of all primary and secondary users, as well as the orientations and parameters of their directional or omni-directional antennas. This paper derives a Maximum Likelihood (ML) algorithm, an approximate ML algorithm, and associated performance bounds for jointly estimating a transmitter's position, orientation, beam width, and transmit power, as well as the environment's path loss exponent, using received signal strength measurements. The methods can be used for either a primary or secondary user. Simulations are used to determine what types of sensor geometries lead to good estimates of each parameter, to evaluate the performance of the estimators, and to determine spectrum availability as a function of spatial coordinates.

S.Kianoush et.al [4] Wireless Body Area Networks (WBANs) have recently received much attention due to the possibility to be used in healthcare applications. For these applications, link reliability and energy efficiency are critical issues, as in many cases, information carried can be vital for the patient and batteries cannot be easily replaced. The wireless on-body channel experiences significant temporal variation due to body movements and the use of relays is sometimes necessary in order to guarantee reliability or improve lifetime. In this paper, an experimental evaluation is used to give a better understanding about reliability, energy consumption and lifetime in a single hop or a two hops communication. This analysis keeps into consideration the correlations between propagation on different links which affect simultaneously the time-varying connectivity on different links of the body. The results shows that an off-body relays could be used to increase data reliability, minimize energy requirements and maximize network lifetime.

A. S. Yunxia Chen and Qing Zhao designed distributed spectrum sensing and access strategies for opportunistic spectrum access (OSA) under an energy constraint on secondary users. Both the continuous and the bursty traffic models are considered for different applications of the secondary network. In each slot, a secondary user sequentially decides whether to sense, where in the spectrum to sense, and whether to access. By casting this sequential decision-making problem in the framework of partially observable Markov decision processes, we obtain stationary optimal spectrum sensing and access policies that maximize the throughput of the secondary user during its battery lifetime. We also establish threshold structures of the optimal policies and study the fundamental tradeoffs involved in the energy-constrained OSA design. Numerical results are provided to investigate the impact of the secondary user's residual energy on the optimal spectrum sensing and access decisions.

III. EXISTING SYSTEM

This system is based on Energy-Efficient Cooperative Localization Algorithm (EE-CLA) for PU positioning using a mobile-aided CR. In which a mobile CR manager is introduced to balance the requirements for positional accuracy and power consumption restrictions by waking up only an appropriate number of CRs collaborating with the mobile CR manager. To investigate the influence of accurate location information, a location-aware CR (LaCR) routing protocol is applied. By employing the mobile CR manager through an energy efficient cooperative algorithm, it provides a sensitive detector even in harsh channel conditions without leading to higher hardware complexity. From an implementation perspective, it leads to the reduced hardware cost and complexity.

In which the localization of CR manager is done by using RSSI received, distance and velocity of the CR manager. RSSI is measured by energy detection based cooperative spectrum sensing and the results are fused at MCR using k out of N rule. Create a local region by keeping CR manager as center. The radius of the circle is obtained by the energy optimization process. The best CR's set within the local region is selected by using cooperative selection. Localization of the PU is done by using best CR's by RSSI received from the PU. Final PU position estimate as the mean positions of PU positions estimate obtained from the each iteration of random way point model. To reduce the energy CR's in local region(circle) is active at a time.

IV. PROPOSED SYSTEM AND DESCRIPTIONS

We consider a CR network composed of N CRs and M PUs. A mobile CR manager is also introduced, as shown in Fig. 1. We employ energy detection based spectrum sensing reports coming from the CRs to detect PU signals in multichannel propagation with shadow fading.

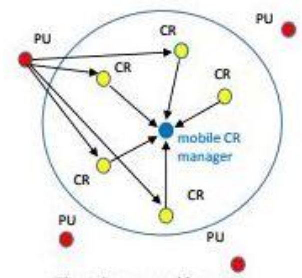


Fig 1. System Architecture

A.Channel propagation

In order to consider multichannel and shadow fading effect, we apply the log-normal model according to

RSSI(i,j) = RSSI(d0) − 10αi,jlog10 (di,j/d0)+ Xs

where RSSIi,j is the received signal at device i from device j. Note that j can be either a CR or a PU, since we use RSSI measurements in two cases: from a CR during the mobile CR manager localization (see Sec. IV.A) and a PU during the PU localization procedure (see Sec. IV.C). RSSId0 is the received signal at reference distance d0 and is equal to the transmission power minus the path loss at reference distance [17], [18]. αi,j is the path loss exponent for the communicating devices i and j. Note that in multichannel condition the value αi,j may be different for each communicating link. di,j is the distance between devices i and j, and Xs is the large-scale shadow fading.

B. Mobile CR manager mobility model

In this paper we use a single mobile node, i.e., the mobile CR manager, moving according to a random waypoint mobility model (RWP) [19]. In general, this model has been classified into four subcategories namely random mobility, controlled mobility, predictable mobility and geographic mobility. According to Gloss et. al. [20], the random waypoint mobility model is the most widely used mobility model for mobile communications research. Indeed, since we apply a geometric based localization algorithm that is sensitive to the anchor nodes (i.e., CRs and the mobile CR manager) deployment in the network, a controlled mobile node trajectory may provide a controlled mobile CR manager deployment that turns out in more accurate localization results [21]. However, this assumption would make the approach limited to a priori knowledge of the mobile CR manager path. Thus, a more generic random way point mobility model is preferred. The mobile CR manager here employs the random way point model that is based on dividing the motion of the mobile CR into pause periods and motion period with random direction [22]. In the pause period, the mobile CR will stay in its current position for a specific period of time. However, in the motion period, the mobile CR will choose a random direction and will start moving to the new direction with a random speed. After arriving in the new position, the mobile CR enters the pause period and stays in that position for the same period of time used in the previous position. In this model, we set some parameters, i.e., mobile CR manager speed, direction, walking time and pause time.

C. Cooperative spectrum sensing

As in conventional cooperative spectrum sensing (CSS) scheme, each cooperative partner CR i makes a binary decision based on its local observation (i.e. the RSSI reports obtained by (1), which are compared with a threshold to decide for the presence or absence of the PU). Then CR i forwards its one-bit decision Di (Di= 1 stands for the presence of the PU, and Di= 0 stands for the absence of the PU) to the mobile CR manager. At the mobile CR manager, all one-bit decisions are fused together according to the logic decision fusion rule [23], [24] and the final decision can be obtained as

$$Y = \sum_{i=1}^{N} D_i \begin{cases} \geq k & H_1 \\ < k & H_0 \end{cases}$$

where H0 and H1 denote the decision made by the mobile CR manager that the PU is present or absent, respectively. The threshold k is an integer, representing the “k-out-of-N” rule. It can be seen that the OR rule corresponds to the case of k = 1, the AND rule corresponds to the case of k = N. Under the “k-out-of-N” rule that we assume, the mobile CR manager declares H1 if k out of N CR users report ‘‘1’’. At mobile CR manager, the detection probability Qd and the false alarm probability Qf for cooperative sensing under this rule is given by [25]:

$$Q_d = Prob[Y > k|H_1] = \\ = \sum_{i=k}^{N} \binom{N}{i} \bar{P}_d^{i} (1 - \bar{P}_d)^{N-i}$$

$$Q_f = Prob[Y > k|H_0] = \\ = \sum_{i=k}^{N} \binom{N}{i} \bar{P}_f^{i} (1 - \bar{P}_f)^{N-i}$$

where P̅d and P̅f are the detection and false alarm probability of the single CR, respectively. Moreover, according to the recent experimental findings, we assume the “on-off” PU activity model has an exponential distribution of the “on” times. Specifically, we assume PU activities with death rate α and birth rate β. From the PU activity model, we can estimate the a posteriori probabilities as follows[26]:

$$P_{on} = \frac{\beta}{\alpha + \beta}$$
$$P_{off} = \frac{\alpha}{\alpha + \beta}$$

where Pon is the probability of the period used by PUs and Poff is the probability of PU idle period. From the definition of maximum a posteriori (MAP) detection [27], PU detection probability Pd and the false alarm probability Pf are given by

$$P_d = Q_d . P_{on}$$
$$P_f = Q_f . P_{off}$$

ENERGY EFFICIENT LOCALIZATION

The energy-efficient wakeup model aims at selecting minimum number of CRs to localize the PU, in order to avoid unnecessary waste of energy to activate all CRs. The mobile CR manager balances the requirements of positional accuracy and power consumption restrictions by waking up an appropriate number of CRs in local regions as explained in the following.

We here focus on the energy consumption in the data acquisition phase to obtain the range measurements through cooperative spectrum sensing for localization. Opportunistic wake up energy modeling is implemented in two main steps: first, defining the local region, and second,computing the opportunistic wakeup probability.

A. Local region definition

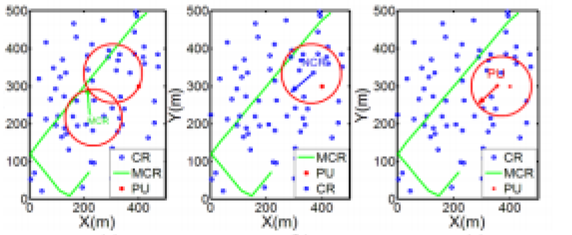
Generally speaking, in cooperative localization, increasingthe number of anchor nodes (i.e., nodes that know their absolute coordinates) improves the localization accuracy, but it is energy demanding due to the high number of message exchange among anchors. Specifically here for PU localization, some CRs act as anchors and a local region is defined to stimulate only local CRs instead of employing all CRs for data collection. On the other hand, reducing the CRs number decreases the localization accuracy. In order to cope with the localization accuracy problem, the mobile CR manager collaborates with the fixed local CRs to provide spatial diversity to localize an unknown PU. Moreover, since the transmission power increases with the forth power of distance1, CRs far from each other require high transmission power to communicate, while CRs that are in the local region, can use lower transmission power to transfer data to the mobile CR manager, thus reducing their energy consumption. Two main approaches are proposed for the local region definition: adaptive and static. The former is defined according to the mobile CR manager location, while the latter is independent from the mobile CR manager. In the adaptive approach, the local region moves along the mobile CR manager trajectory, while in the static approach, the local region is fixed and specified by the approximate location of the PU or the closest CR neighbor to the PU.

i. Adaptive approach

In the adaptive approach the local region is defined arbitrarily at the beginning but is subsequently modeled according to the mobile CR manager mobility information. Since the mobile CR manager starting point is unavailable to the network, it is approximated using the Min-Max algorithm and the three closest CRs to the mobile CR manager corresponding to those with the highest RSSI values [28]. RSSI range measurements are obtained by both CRs and mobile CR manager. Once the mobile CR manager starting point is estimated, an initial local region is shaped as a circle around the mobile CR manager and limited by the optimum local region radius (which we assume to be equal to the transmission radius). The local region radius is obtained through the energy optimization process described in Sec. IV.D. During the mobile CR manager movement, its displacement from the starting point can be obtained. If the mobile CR manager remains inside the initial local region, the previous local region is exploited for the new mobile CR manager position and the local region does not change. Changing the local region consumes energy because the local CRs inside the new local region should change from their idle mode to the active mode. This approach avoids changing the local region frequently and thus the energy consumption is reduced. If the mobile CR manager leaves the current local region, the local region location is updated using the mobile CR manager current location information. Although the mobile CR manager position may not be extremely accurate, it is used here only to shape the local region. The algorithm runs along the mobile CR manager trajectory and local regions are obtained adaptively. Note that, since CRs are randomly deployed, the number of CRs within a given local region may be different even if the local region size is constant. Fig. 2 (a) presents the adaptive local region. Since the local CRs inside a local region are not the same CRs inside another local region, the localization result using the local CRs is robust to the geometric constraints. For example, several estimations with different accuracies are obtained for the PU localization using the adaptive local regions. As a matter of fact, if the local region were fixed, always the same local CRs would be used for localization, there would be no diversity in geometry and the localization error could be large, especially for a local region placed in one of the area corner. Another advantage is that the adaptive approach can be easily generalized to multiple PUs localization.

ii. 2. Static approach

The static approach is a specific case of the adaptive approach in which the target in not the mobile CR manager, but an approximate PU location or the position of the CR closest to the PU, which is fixed. With the static approach, we consider two different ways to define the local region. In the first case, the region is centered in position of the CR closest to the PU, named nearest CR, which corresponds to the CR with the highest RSSI value from PU. In the second case, the region is centered on the initial estimate of the PU. Fig. 2 (b) shows the first approach, in which the local region is centered on the nearest CR position. In this case, the CRs in the local region are fixed and do not change. This approach is fast in comparison with the adaptive approach. Fig. 2 (c) shows the second option where the local region is centered in the initial PU position estimate. Although this option is static, it can be adopted in case of a mobile PU. In this case the static approach becomes adaptive and the local region would follow the mobile PU, by waking up any local CR in the PU local region.



(a) (b) (c)

Fig. 2 Local region definition (a) adaptive approach, (b) local approach using the nearest CR position (c) local approach using the PU position estimate. MCR refers to the mobile CR manager and NCR refers to the nearest CR to PU.

B. Opportunistic wakeup probability computation

Once the local regions are obtained, we need to measure the distances between the PU and the CRs using the energy detector reports. Since the CRs outside a local region are redundant for the localization algorithm, the unnecessary CRs can be shut down, still ensuring a sufficient number of local CRs for localization. This idea is initially inspired by the selection of the local CRs and the probabilistic wakeup protocol [16]. Indeed, we manage to reduce the number of active local CRs and the communication overhead among the local CRs, thus contributing to energy saving of the entire network. Anyhow, in sleep mode, the local CRs can exchange opportunistic data, so that they can regulate their on and off states to complete localization. As known, in two-dimensional space, we need minimum three reference local CRs' location information to locate the PU [7]. Assuming that the local CRs are independent, if the number of local CRs used in the localization process l≥3, the probability of minimum requirement to locate the PU obeys the binomial probability Preq(n, pw), where n represents the number of the local CRs in a local region, and pw represents the wakeup probability of the local CRs. Given the hypothesis that there is not ambiguous in the CRs deployment (i.e. two or three CRs are not aligned, etc.), the localization probability using the improved trilateration algorithm is equal to 0.9 [29]. Thus the probability PPÛ of locating the PU can be approximated with Preq [30], where Preq given by

$$P_{req} = P(l \geq 3) = 1 - P(l=0) - P(l=1) - P(l=2)$$
$$= 1 - \binom{n}{0}(1-p_w)^n - \binom{n}{1}p_w(1-p_w)^{n-1} + -\binom{n}{2}p_w^2(1-p_w)^{n-2}$$

in which l represents the number of local CRs to involve for localization [16]. Finally, since we perform the PU localization procedure only if the detection through cooperative spectrum sensing has given positive feedback, the probability of locating the PU can be expressed as:

PPÛ = Pd · Preq

where Pd and Preq given by (6) and (7) respectively.

At any time, the probabilityPPÛ of locating the PU must satisfy a minimum value λ, i.e.PPÛ ≥ λ.

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In Fig. 3 we show the pw values versus local CRs number for different values of the localization probability threshold λ. The figure easily shows that the wakeup probability value changes with the local CRs number: a higher number of local CRs consumes more energy for communication while decreasing the wakeup probability of the local CRs balances the energy consumption due to reduction of the local CRs number. Note that, in order to increase the local CRs number in a local region, we may increase the total number of CRs nT if we assume an uniform distribution, and/or the local region radius r (which we assume to be equal to the CR transmission range). The former increases the local CRs number in a local region with a specifier, regardless of the way the local region is defined, while the latter enlarges the local region so that more local CRs can communicate. According to (7) and (8), we can map the quantitative relation between the number of local CRs and PPÛ . In order to reverse (7) to compute the wakeup probability pw for a given value of λ, we ran some simulations to obtain the unctional relationship between the wakeup probability and the number of local CRs.

A curve fitting technique has been used to get the relation between the wakeup probability and the number of local CRs for a given localization probability as shown in (9):

$$p_w = ae^{bn} + ce^{dn}$$

Simulations showed that the wakeup probability can be approximated by (9), with local CRs n between 10 and 35 for different values of the coefficients a, b, c, d reported in TABLE I

TABLE I
COEFFICIENTS OF THE EXPONENTIAL FIT FOR THE WAKEUP PROBABILITY AS A FUNCTION OF LOCAL CRS FOR THREE DIFFERENT POSITIONAL PROBABILITY THRESHOLD VALUE.

coefficient	*λ=0.8*	*λ=0.85*	*λ=0.9*
a	0.9731	2. 918	0.7469
b	-0.181	-0.3926	-0.057
c	0.2965	0.6075	0.1834
d	-0.0233	-0.051	-0.174

C. Channel and distance estimation

In CRNs, PUs and CRs do not collaborate, so channel parameters are not available in a CR network. In order to estimate the channel parameters, we use range measurements in a noisy channel propagation exploiting smoothing and fitting curve techniques. Specifically, fixed CRs collect different records of RSSI measurements from PUs through spectrum sensing in harsh channel condition, as modeled in (1). For each CR we obtain RSSI measurements at different distances from PUs. Then a smoothing technique, i.e., loess-local regression method, is applied to smooth noisy RSSI measurements. We use loess-local regression smooth method since it is resistant to outliers, i.e., RSSI records whose value is significantly different from the other collected measurements [31]. Once smoothed RSSI measurements are obtained, a logarithmic fit curve is applied to the smoothed RSSI measurements with 0.95 confidence intervals. Then RSSId0 (calculated at d0=1 m), and αi,j for each communication link i-j are obtained by interpolation. At the end, based on the estimated channel parameters and the log-normal model in (1), the distance between CR i and PU j are subsequently estimated according to

$$\hat{d}_{i,j} = 10^{\left(\frac{\bar{R}SSI_{d0} - RSSI_{i,j}}{10 \times \hat{\alpha}_{i,j}}\right)}$$

ENERGY EFFICIENT COOPERATIVE LOCALIZATION

In order to determine the PU position, the mobile CR manager calls the localization service. After obtaining the number of the local CRs and opportunistic wakeup probability computation, the mobile CR manager is first localized by the fixed CRs, since we assume its positions are unknown, and then it collaborates with the other local CRs for PU localization.

A. Mobile-aided localization

In order to reduce communication overhead and energy consumption, a mobile CR manager is here exploited. It balances the requirements for high PU localization probability and power consumption restrictions by waking up an appropriate number of CRs in local regions through a cooperative algorithm. Additionally, in order to determine the PU location accurately, the mobile CR manager acts as an anchor node providing spatial diversity, due to its mobile path, and cooperating with the fixed CRs to estimate the PU position. More specifically, the mobile CR manager receives RSSI reports from few fixed GPS-equipped local CRs to estimate its own distance to the local CRs according to (10), in which the channel parameters are estimated with the procedure described in Sec. III.C. Then the distance estimates are used along with a velocity algorithm [28] to obtain the mobile CR manager position. The velocity algorithm relies on the history of movements, i.e., the previous positions of the mobile CR manager (obtained by Min-Max algorithm in noisy channel) and a linear prediction model of the mobile CR manager speed. The speed Vm is estimated using a moving window corresponding to the past history of the previous estimation of the mobile CR manager position CR Pm. where tm is the m-th time stamp to filter out outlier estimations. A refined estimation of the mobile CR manager location is then calculated through a comparison of the previous estimated mobile CR manager position and the bound. If the newest estimation falls outside the bound, then the measure might be affected by noise:the actual position is assumed to be along the direction of the estimated point, but inside the bound and not farther [28], otherwise the mobile CR manager position estimates is considered to be already accurate.

B. Cooperative selection of the best local CRs set

Based on an opportunistic wake up model, the cooperative localization scheme regulates the CRs' on-off states through changing the wakeup probability of each CR in different local regions. Also, it ensures that the number of active CRs is large enough for a given PU localization probability [16]. Among these CRs, the mobile CR manager finds the best local CRs set inside each single local region to estimate the PU position through a cooperative algorithm, as described in the following. The best set of local CRs that collaborates to estimate the PU position is the set of local CRs that gives the minimum PU localization error. Since the PU does not cooperate with the local CRs while messages may exchange among local CRs, we consider the position estimation of the nearest CR to the PU to calculate the best set of local CRs for PU positioning. In fact, by geometric consideration, the best local CRs set for the nearest CR positioning will be also the best set for PU positioning. Let us assume that the nearest CR position is unknown, while other nodes in its transmission range have known position. The nearest CR position can be estimated using any triplet of local CRs, but only one is the best local CRs set.

To this purpose, we apply the Min-Max localization technique by using local CRs positions and distances between each other by using (10). The local CRs set with minimum localization error for the nearest CR positioning is considered as the best local CRs set. Note that the local CRs set may be composed by local CRs with fixed position and/or different positions of the mobile CR manager along its path. In general the accuracy of a localization algorithm increases with the number of CRs involved in the collaboration process, and on this purpose usually a large number of GPS-equipped CRs are used [9]. On the contrary, we here consider different positions of a mobile CR manager and few local CRs with known position, thus reducing energy and cost constraints. Also finding the best local CRs set improves the localization accuracy, which is then used for the LaCR protocol in Sec. V. The LaCR protocol exploits the localization accuracy information for CR power adaptation, channel selection and routing scheme. The best local CRsset is used for PU positioning as explained in the following.

C. Primary user localization

In order to localize the PU position, we exploit the best local CRs set and an Improved Min-Max estimator. We run RWP mobility model iteratively to have different random paths of the mobile CR manager. Each iteration gives a PU position estimate obtained by Min-Max estimator using the best local CRs set, thus at the end of iterations, different PU position estimates are obtained. Some of these PU estimates are discarded by an outlier technique, i.e., proximity level [32]. The final PU position estimate is calculated as the mean of the remaining PU positions estimates. Specifically, let us assume that we perform several position estimations before taking the final decision. An outlier is an estimated position that is far away from the other position estimates. Proximity level approach focuses on the distance among the estimated positions in the "dense" area, i.e. the area where the most position estimates fall in. Suppose there is an underlying distance metric function that gives the distance between any pair of estimated positions. For an estimated position , the dr-neighborhood of contains the set of objects that are within distance dr from [32]. In fact, there is high probability that the closest estimates to each other are also close to the exact PU position, thus we select only PU position estimates within dense neighborhoods. In particular, the value dr has to be chosen carefully and here is obtained by some experiments. Its value depends on the value σnoise of the shadow fading. Specifically, we set dr=2 and dr=5 m in large scale areas, i.e., 100×100 m and 500×500 m, respectively, for a realistic scenario where σnoise=6dB in indoor environment. Once dr is defined, the current PU position is compared with other PU estimates obtained over a different mobile CR manager path and the weight zero or one is assigned according to the following procedure: if the distance between the current PU position estimate and the other available PU estimates is lower than dr, then the weight w is equal to one, otherwise it is set equal to zero. We define the value of the proximity level as the number of positions where w is set to one. For each PU position estimate, a matrix is assigned that contains k PU position estimates and their weights w referred to the current estimate. Then, the matrix with maximum proximity level is selected. Finally, the final PUposition Pˆ PU is calculated as the mean of the PU positions estimate Pi^PU with maximum proximity level according to (11).

$$\hat{P}^{PU} = \frac{\sum_{i=1}^{k} w_i \hat{P}_i^{PU}}{\sum_{i=1}^{k} w_i}$$

where k is the number of the PU position estimates PiˆPU of the selected matrix. In this way the outliers are automatically discarded and the localization performance improves.

D. Energy consumption

To estimate the energy consumption, the proposed work focuses on the energy detection based approach that collects RSSI measurements for localization. In data acquisition phase, active local CRs communicate with each other within the local region. This operation turns out in energy consumption, and Eq corresponds to the energy consumption of the local CRq that is communicating. According to our approach, the energy consumption for a given local CRq in a particular local region l is the product of Eq and pwl. Note that pwl value is constant for all local CRs within the local region l. The total energy consumption in data acquisition phase is obtained using (12) by considering all L local regions.

$$E = \sum_{l=1}^{L} \sum_{q=1}^{Q} E_q \times p_{wl}$$

As shown in (12), the total energy consumption in the network depends on the value of pwl that is also connected to the local region radius r (which is also the value of the transmission range) and the localization probability P^PU , as shown in Sec III.B.

Finally, to find the values of r and P^PU that minimize the energy consumption, the optimization problem is therefore formulated as

$$\min_{r,\, P_{\widehat{PU}}} E$$

so that:

$$P_{\widehat{PU}} \geq \lambda$$
$$r \geq \tilde{r}$$

The value r˜ guarantees that i n the local region there is the minimum number of CRs to localize the PU and the threshold λ is the required PU localization probability threshold. Thevalue of the localization probability PPÛ depends on the localization algorithm applied for the PU localization. For example, the localization probability for the geometric based localization algorithm used in Sec. IV. C is equal to 0.9 [29]. The energy consumption optimal surface corresponding to the r and PPÛ parameters is applied. The minimum energy consumption for a given r and PPÛ can be obtained on such optimal surface. Note that we exploit the optimum value r̃ for the local region definition in Sec III.A. We here summarize the procedure through its pseudo code. Specifically, Algorithm I and II represent the EE-CLA localization and energy consumption procedures.

APPLICATION TO THE LOCATION AWARENESS ROUTING PROTOCOL

We here exploit the knowledge of PUs location to improve the performance of CR power adaptation, channel selection and routing scheme. The proposed location-aware CR (LaCR) routing protocol [5] is here briefly described and the performance improvement in terms of CR end-to-end performance and PUs collision risk are then detailed in Sec.VI. Let us assume a CR ad hoc network with a common control channel (CCC) used during routing formation. The CCC is also used by CRs to share the information about the environment, such as detected heterogeneous PUs and their features, together with their location. Such information is useful to calculate the achievable rate in a certain location area. The process to identify free bands and PU types [33] is not detailed in this paper because it is out of the scope of this work. Specifically, the area is divided into clusters according to similar spectral characteristics. After classifying the existing PUs, CRs extract PU features, such as bandwidth and allowable interference level, which directly influence the achievable rate in a certain cluster [34]. In this work, in addition to these features, a third one is considered, i.e. the location of PU. Such information can be used to efficiently adapt CR transmission power to better avoid the harmful interference to the primary network. We here exploit the localization to adapt CR transmission power and assist the routing protocol. After calculating the achievable rate for each cluster according to [34], the LaCR routing protocol is developed. The proposed approach accounts also for the localization error. The LaCR routing protocol consists in two steps: intra-cluster and inter-cluster procedures. In particular, in our system we assume that there are similar spectral characteristics different locations in a certain cluster. Thus, the intra-cluster procedure selects the path only depending on location information and available spectrum bands in the cluster, while the inter-cluster procedure selects the path also according to different spectral characteristics among clusters.

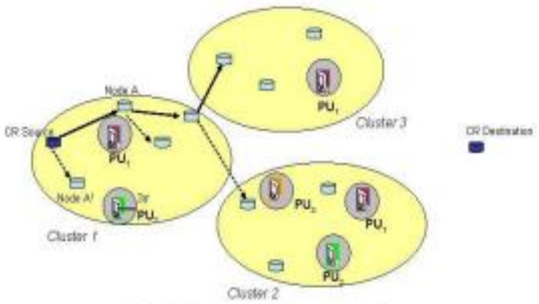

Fig. 4 LaCR routing protocol

A. Intra-cluster protocol

The intra-cluster protocol is composed of two stages: (1) path& spectrum selection, and (2) power adaptation.

1) Path & spectrum selection: During the path selection we choose the next node to realize a multi hop transmission. In particular, we select the node with the greatest advance in the cluster that is in the transmission range of the CR source node. Then, the spectrum selection is carried out with the objective to minimize the interference towards the PU. Thus, the spectrum band of the farthest PU from CR source node is selected. As an example, focusing on the first cluster in Fig. 4, let us assume that there are only two available spectrum bands, i.e.b1 and b2, and the primary users PU1 and PU2 can transmit on spectrum b1 and b2, respectively. At the CR source node, the choice as next hope can be node A or node A'. Since we assume there are similar spectral haracteristics at different locations inside a given cluster, in both cases the available spectrum are b1 and b2. The choice depends on the furthest advance in the cluster, thus node A will be selected. Once the next hop is selected, the spectrum is chosen according to the distance between the CR source node and the PUs. Specifically, the spectrum b2 will be selected since the primary user PU2 on spectrum b2 is farther than the primary user PU1 on b1. At this stage, the power adaptation process is carried out.

2) Power adaptation: Our objective is to increase CR rate by maximizing CR transmission power and avoiding PU interference. On this purpose, PU location information is efficiently exploited. However, since some localization error may occur, we do not consider that the PU is in a deterministic point, but inside a circle of radius 3σ, as shown in Fig. 5. In particular, $\sigma^2 = E\left[\left\|\hat{p}^{PU} - p^{PU}\right\|_2^2\right]$ is the variance of thelocalization error $\Delta d = \left\|\hat{p}^{PU} - p^{PU}\right\|_2$, in which p^PU is the estimated position of the PU and PPUis the real position. The proposed EE-CLA localization method shows a normal distribution of the error on each axisΔx and Δy (verifiedthrough simulation in Sec. VI.B2). Therefore Δd has a Rayleigh distribution,

$$\Delta d = \left\|\hat{p}^{PU} - p^{PU}\right\|_2 = \sqrt{\left(\hat{p}_x^{PU} - p_x^{PU}\right)^2 + \left(\hat{p}_y^{PU} - p_y^{PU}\right)^2} = \sqrt{\Delta x^2 + \Delta y^2}$$

Hence, there is probability that the PU lies in a circle of radius 3σ. In more details, we want to maximize CR transmission power given the interference constraint:

$$I_{PU}(P_{CR}(j^*)) = k_0 P_{CR}(j^*) / (d_{CR\text{-}PU}(j^*) - 3\sigma)^{\alpha} \le I_{th}(j^*)$$

where k0 and α are the path-loss coefficient and exponent, dCR−PU is the distance between the CR transmitter and the PU on the selected spectrum band j*, and Ith(j*) is the interference level allowed by the specific PU. In particular, Ith may have different values according to PU type. To understand the improvement achieved by considering PU localization in CR power adaptation, we compare the distance dCR−PU between CR transmitter and PU and the sensing radius rs (see Fig. 5). An improvement may arise:

- if the distance dCR−PU is greater than the sensing radius rs,i.e. the PU is far from the CR. In this case, the conventional assumption when considering only the sensing information of the given CR, is to consider that the PU is just at an rs distance from the CR to prevent any harmful interference to the primary system. On the contrary, by knowing PU location obtained through a collaborative solution, such as EE-CLA, it is possible to increase the CR transmission power

$$d_{CR\text{-}PU}(j^*) > r_s + 3\sigma$$

$$\Delta P_{CR}^{*} = \frac{I_{th}(j^*)(d_{CR-PU}(j^*) - 3\sigma)^{\alpha}}{k_0} + \\ - \frac{I_{th}(j^*)}{k_0}(r_s - 3\sigma)^{\alpha}$$

- if the distance dCR−PU is smaller than the sensing radius rs, i.e. the PU is close to the CR. In this case, in the classical formulation without considering the distance, the CR does not transmit, while we assume

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that the CR can transmit with a lower transmission power according to the interference threshold Ith and the distance dCR−PU. Thus, the improvement in this situation is expressed as

$$r_s > d_{CR-PU}(j^*) > 3\sigma$$

$$\Delta P_{CR}^* = P_{CR}^* = \frac{I_{th}(j^*)}{k_0}(d_{CR-PU}(j^*)-3\sigma)^\alpha$$

The intra-cluster procedure is repeated several times in the cluster in order to select the next node of the route and its spectrum. If no such node exists then the inter-cluster procedure is carried out.

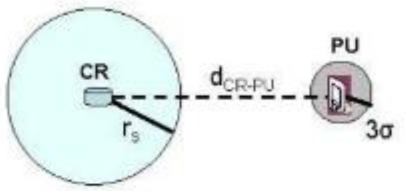

Fig. 5 Localization improvement

B. Inter-cluster protocol

To select the next hop in the inter-cluster procedure, we choose the node of the cluster m with the maximum achievable rate Rc(m), calculated according [34]. Given different spectral characteristics in different clusters, the achievable rate in each cluster will change accordingly. As an example, let us consider cluster 2 and cluster 3 in Fig. 4, which have different spectral characteristics so that Rc(3)>Rc(2). Thus, the node in cluster 3 will be selected for the next hop, and the intra-cluster procedure will be carried out in cluster 3.

C. Interference due to localization error

In case of localization error, CR transmissions may cause interference to PU. Specifically, it happens when the actual PU position is outside the circular region of radius 3σ (Fig. 5). As a result, the interference constraint expressed in (15) is not satisfied and the interference suffered by PU IPU at spectrum j* becomes

$$I_{PU} = \frac{k_0(I_{th}(j^*)(d_{CR-PU}(j^*)-3\sigma)^\alpha / k_0)}{(d_{CR-PU}(j^*)-3\sigma-\varepsilon)^\alpha}$$

where the term accounts for the actual PU position outsidethe circular region of radius 3σ. In other words, the variance σ2 of the localization error influences the performance of the LaCR routing protocol. Since the proposed EE-CLA localization algorithm shows good performance in terms of localization accuracy and error variance, the LaCR routing protocol will benefit from it.

ENERGY HARVESTING METHOD

Localization of the PU is done by using best CR's by RSSI received from the PU. The best CR's set within the local region is selected by using cooperative selection. In which all the CRs in the CRs set is active at a time. To reduce energy, only one CR in the CRs set should active at a time. For this, a time slot is provided for each CR to access the channel. By this method, we can increase accuracy and also the efficiency.

V. SIMULATION RESULT

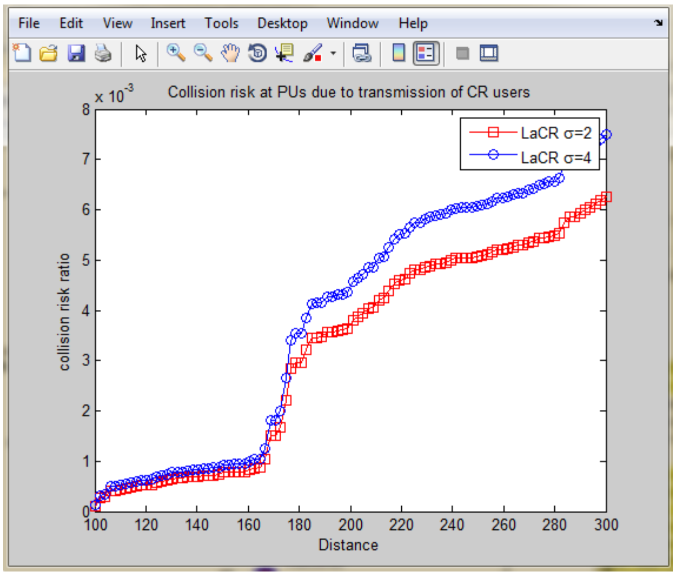

Fig 6. Collision risk at Pus due to transmission of CR users.

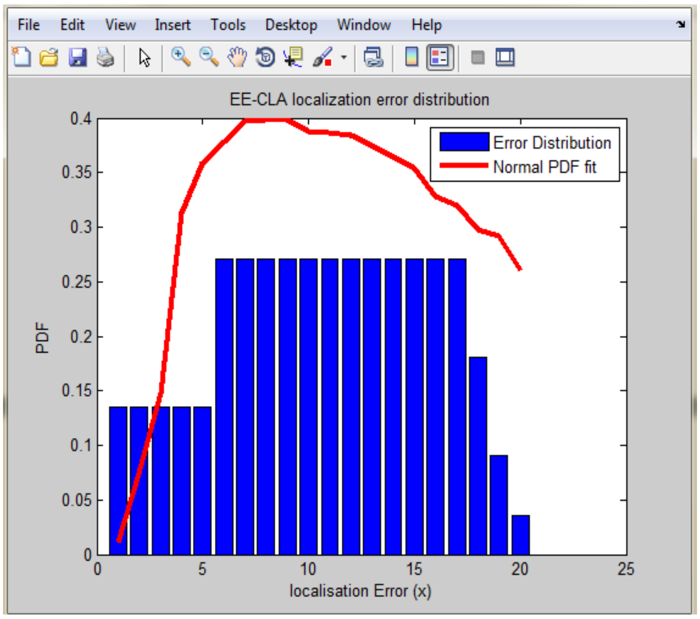

Fig 7. EE-CA localization error distribution

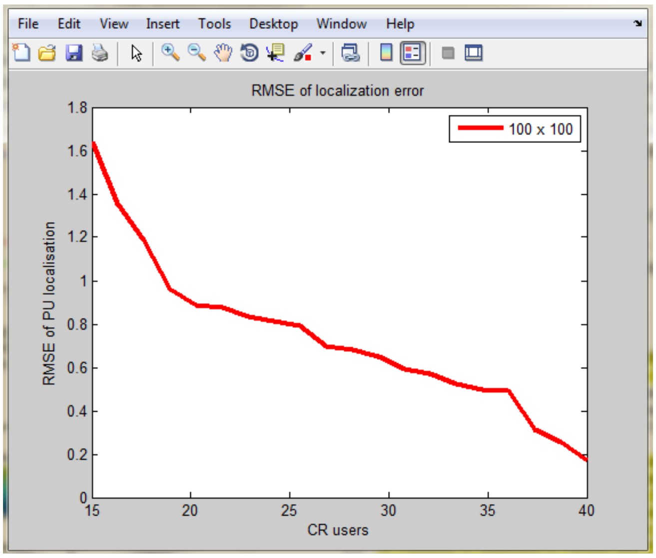

Fig 8. RMSE of localization error

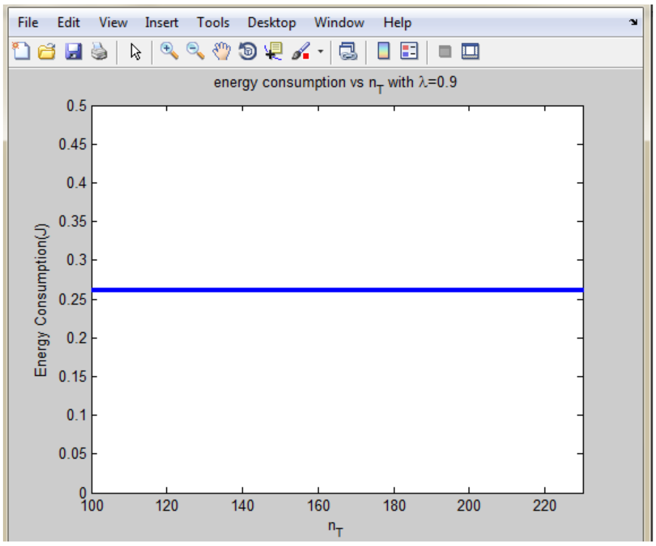

Fig 9. Energy consumption vs Nt with λ=0.9

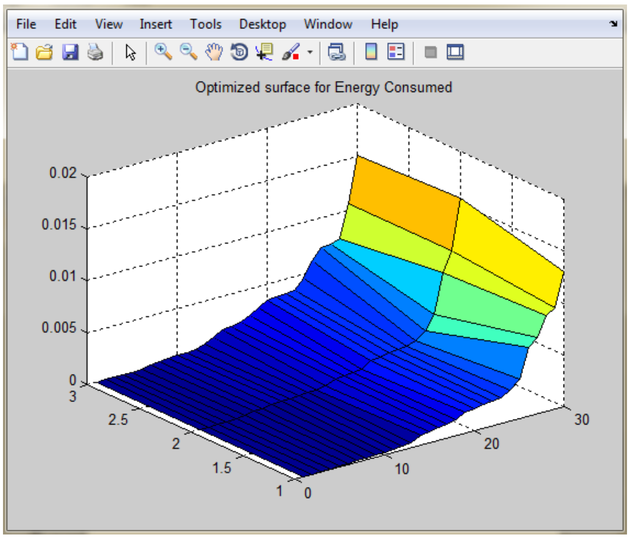

Fig 10. Optimized surface for energy consumed.

VI. Conclusion

In localization solutions for CR networks, the challenge is to reduce energy consumption while maintaining localization precision. The cooperative localization algorithm, named CLA, provide an accurate estimation of PU position in harsh channel condition while consume more energy than generic non cooperative localization approaches. In order to overcome this issue, we propose an EE-CLA algorithm that defines a local region to select the CRs to be active. CRs' on-off states for different local regions are regulated through changing the wakeup probability of local CRs dynamically. Furthermore, it employs a mobile CR manager that collaborates with other active CRs to compute the wakeup probability and PU position. In this approach the CRs inside a local region collaborate to localize the PU while the rest of the CRs remain in sleep mode. Results confirm that the number of CRs inside the local region is reduced, and localization result is still accurate. Moreover, under shadow fading, the EE-CLA localization algorithm outperforms the CLA algorithm in terms of energy consumption during the data acquisition phase. To illustrate the benefits of localization, a location aware CR routing protocol has been also implemented. Simulation results show the effectiveness of the proposed approach in terms of CR end-to-end performance and PU protection.

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