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Cooperative spectrum sensing and data transmission optimization for multichannel cognitive sonar communication network

Xin Liu^{1*} and Min Jia²

Abstract

The natural acoustic system used by marine mammals and the artificial sonar system used by humans coexist in the underwater cognitive sonar communication networks (CSCN). They share the spectrum when they are in the same waters. The CSCN detects the natural acoustic signal depending on cooperative spectrum sensing of sonar nodes. In order to improve spectrum sensing performance of CSCN, the optimization of cooperative spectrum sensing and data transmission is investigated. We seek to obtain spectrum efficiency maximization (SEM) and energy efficiency maximization (EEM) of CSCN through jointly optimizing sensing time, subchannel allocation, and transmission power. We have formulated a class of optimization problems and obtained the optimal solutions by alternating direction optimization and Dinkelbach's optimization. The simulation results have indicated that SEM can achieve higher spectrum efficiency while EEM may get higher energy efficiency.

Keywords: Cognitive radio, Cooperative spectrum sensing, Spectrum efficiency, Energy efficiency

1 Introduction

Cognitive radio (CR) can improve spectrum utilization greatly through letting secondary user (SU) to access the idle spectrum licensed to the primary user (PU) [1]. However, the SU has to detect the absence of the PU through performing spectrum sensing, in order to guarantee the normal communications of the PU [2]. Energy detection is widely used as an effective spectrum sensing method due to the unnecessary prior information of the detected signal [3]. But the performance of energy detection will decrease if the PU is in fading or shadowing path, which is called "hidden terminal problem." Cooperative spectrum sensing has been proposed to cope with this problem through letting multiple SUs detect the PU and exchange the sensing information collaboratively [4].

Recently, underwater communication network has attracted the attention, which can be used in underwater environment monitoring and submarine resource exploration. The underwater communication network transmits data using the underwater acoustic channel [5].

However, there are often multiple different underwater acoustic systems in the same water area, which may cause the interference to each other. In order to improve the spectrum utilization, CR has been introduced in the underwater communication network, called as cognitive sonar communication networks (CSCN) [6]. CSCN can use the sonar nodes to detect the presence of the other underwater acoustic systems in the surrounding water environment and transmit data on the premise of detecting the idle underwater acoustic channel. The underwater acoustic environment in the ocean is very complex, and usually, multiple acoustic systems coexist in the same water area, such as artificial echolocation systems, monitoring systems, and the nature acoustic systems of marine mammals [7]. The spectrum sharing of artificial acoustic network system and natural acoustic system will affect the transmission efficiency and the survival of marine mammals. The CSCN can realize the coexistence of a variety of artificial underwater acoustic systems in the protection of marine animals [8]. Thus, in the CSCN, the sonar node and the nature acoustic system can be seen as a SU and a PU, respectively.

Spectrum efficiency is an important index to evaluate the transmission performance of CSCN. Most of the

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previous works focused on optimizing either cooperative sensing or data transmission to maximize the spectrum efficiency of the CSCN. For instance, the listening-before-transmitting spectrum access is proposed, which can maximize the spectrum efficiency through optimizing sensing time [9]; both [10] and [11] assumed that each SU had a fixed transmission power, which ignored the potential gain of dynamic resource optimization. The water filling algorithm could maximize the spectrum efficiency of multichannel CSCN through optimizing subchannel power [12]. Recently, green communications have attracted the attentions of the scholars. Energy efficiency has been proposed to measure the effectiveness of energy utilization [13].

In this paper, we investigate the joint parameter optimization of cooperative spectrum sensing and data transmission for multichannel CSCN. The contributions of the paper are listed as follows:

- We seek to maximize spectrum efficiency and energy efficiency of CSCN, respectively, while considering both spectrum sensing performance for detecting the nature acoustic system and the power constraint of each sonar node.
- We have formulated the cooperative spectrum sensing and data transmission optimization as a class of optimization problems about sensing time, subchannel allocation, and transmission power. In the optimization problem, the nature acoustic system is fully protected, while the transmission performance of the CSCN is improved as much as possible.
- The joint optimization algorithm is proposed to obtain the solutions to the optimization problems, which is based on the alternating direction optimization and the Dinkelbach optimization.

2 System modeling

We consider L nature acoustic systems occupying L subchannels, which are seen as PUs and a CSCN constituting of N sonar nodes, which are seen as SUs. We also suppose that in an artificial acoustic system, there is an access point that controls the channel usage of the SUs in the locating water, which can be seen as a fusion center. In order to avoid causing harmful interference to the PU, the SU has to detect the utilization state of the licensed spectrum and decide the activation of the PU. Hence, the periodic cooperative spectrum sensing based on “listening before transmitting” is proposed in this paper, which divides the communication time into several frames, each of which constitutes of three time slots including local sensing slot, cooperative interaction slot, and data transmission slot, as shown in Fig. 1. In the local sensing slot, all the SUs sense the activation of the PU in L subchannels and obtain the local sensing information.

Then, in the cooperative interaction slot, each SU uses one common channel to report the local sensing information to the fusion center, which makes a final decision on the activation of the PU by the soft-decisional combination of the local sensing information. To avoid the mutual interference, the SUs cannot report from the common channel simultaneously at the same time. Hence, in order to save the bandwidth of the common channel, the SU adopts time division multiple access (TDMA) to report the local sensing information. Finally, in the data transmission slot, the SUs access the licensed spectrum to communicate according to the decision result of the fusion center.

2.1 Underwater acoustic channel model

The fusion center maintains a collection of free channels and the corresponding channel gain matrix in the underwater acoustic region by scanning and spectrum sensing. Supposing that $h_{n,l}$ is the channel gain of SU n using subchannel l , the channel gain matrix \mathbf{H} , can be given by

$$\mathbf{H} = \begin{pmatrix} h_{11} & h_{12} & \cdots & h_{1N} \\ h_{21} & h_{22} & \cdots & h_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ h_{L1} & h_{L2} & \cdots & h_{LN} \end{pmatrix} \quad (1)$$

Due to the reflection of the sea surface, submarine, and underwater medium, there are complicated multipath propagation in shallow sea acoustic channel, which can be considered as generalized uncorrelated scattering condition in general wireless channel. When the number of multipaths is relatively large, the underwater acoustic channel obeys the Rayleigh distribution. Thus, the channel gain distribution is given by

$$f_{h_{n,l}}(h_{n,l}) = \frac{1}{\bar{h}_{n,l}} \exp\left(-\frac{h_{n,l}}{\bar{h}_{n,l}}\right) \quad (2)$$

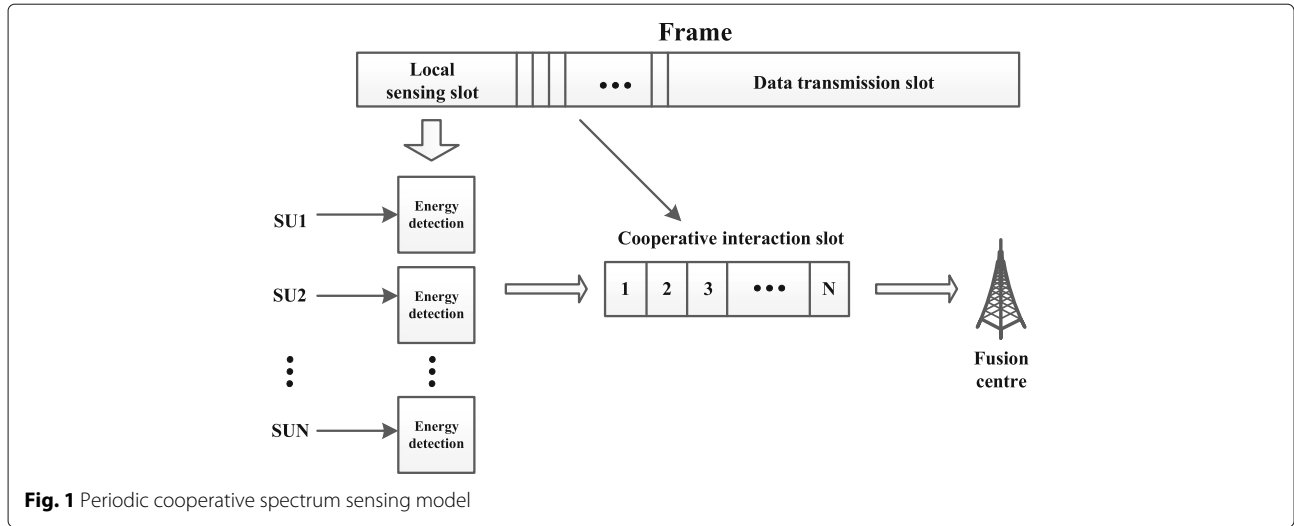
where $\bar{h}_{n,l}$ is the statistical average of $h_{n,l}$.

2.2 Cooperative spectrum sensing

The sensing signal of SU n for $n = 1, 2, \dots, N$ in subchannel l for $l = 1, 2, \dots, L$, $y_{n,l}(m)$, is denoted as follows:

$$y_{n,l}(m) = \theta_l h_{n,l} p_l^s(m) + \sigma_l^2(m), m = 1, 2, \dots, M \quad (3)$$

where $\theta_l = 0$ and $\theta_l = 1$ denote the absence and presence of the PU in subchannel l , respectively; $h_{n,l}$ denotes the subchannel gain from SU n to the PU; p_l^s is the transmission power of the PU in subchannel l ; σ_l^2 is the power of the noise in subchannel l ; and M is the number of the samplings. M is given by $M = \tau f_s$, where τ is the local sensing



time and f_s is the sampling frequency. We can get the energy statistic of the sensing signal $y_{n,l}$ by accumulating the energy of M samplings as follows:

$$\psi_{n,l} = \frac{1}{M} \sum_{m=1}^M \|y_{n,l}(m)\|^2 \quad (4)$$

Each SU reports $\psi_{n,l}$ to a fusion center, which combines $\psi_{n,l}$ of N SUs to get an overall energy statistic of the PU signal in subchannel l as follows:

$$\Psi_l = \frac{1}{N} \sum_{n=1}^N \psi_{n,l} = \frac{1}{MN} \sum_{n=1}^N \sum_{m=1}^M \|y_{n,l}(m)\|^2 \quad (5)$$

The overall energy statistic Ψ_l is compared with a threshold λ . If $\Psi_l \geq \lambda$, the presence of the PU is detected; otherwise, the absence of the PU is determined. When M is large enough, Ψ_l obeys the Gaussian distribution approximately according to the central limit theorem. Hence, the cooperative probabilities of false alarm and detection for subchannel l is given as follows:

$$\begin{aligned} Q_l^f &= Q\left(\left(\frac{\lambda}{\sigma_l^2} - 1\right)\sqrt{N\tau f_s}\right) \\ Q_l^d &= Q\left(\left(\frac{\lambda}{\sigma_l^2} - \bar{\gamma}_l - 1\right)\sqrt{\frac{N\tau f_s}{(\bar{\gamma}_l + 1)^2}}\right) \end{aligned} \quad (6)$$

where $\bar{\gamma}_l = \frac{1}{N} \sum_{n=1}^N \frac{p_l^s h_{n,l}^2}{\sigma_l^2}$ is the average sensing SNR of N SUs in subchannel l , and the function $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} \exp\left(-\frac{z^2}{2}\right) dz$.

In order to avoid causing harmful interference to other underwater acoustic systems, the detection probability

must be guaranteed. The sensing threshold λ can be obtained by fixing Q_l^d with some value, which is given as follows:

$$\lambda = \left[Q^{-1}\left(Q_l^d\right) \sqrt{\frac{(\bar{\gamma}_l + 1)^2}{N\tau f_s}} + \bar{\gamma}_l + 1 \right] \sigma_l^2 \quad (7)$$

The selection of sensing threshold is important to the sensing performance. The detection probability will improve with the increasing of sensing threshold; however, the false alarm probability will also increase, thus decreasing the spectrum access probability. Through removing the threshold λ , Q_l^f is denoted by Q_l^d as follows:

$$Q_l^f = Q\left(Q^{-1}\left(Q_l^d\right) (\bar{\gamma}_l + 1) + \bar{\gamma}_l \sqrt{N\tau f_s}\right) \quad (8)$$

In underwater, since the channel between the signal source and the sonar is often in severe fading, the received signal by one sonar may be too weak to be detected accurately. However, with cooperative spectrum sensing, the same signal can be received by multiple sonars from different paths. If the received signal by one sonar is too weak, the detection performance cannot be decreased through sharing the sensing information with the other sonars. Thus, the sensing diversity gain can be achieved to improve the final detection performance through cooperative spectrum sensing.

2.3 Spectrum efficiency maximization (SEM)

Spectrum efficiency is an important indicator to evaluate the spectrum sensing performance. In spectrum sensing, the decreasing of detection performance may decrease the spectrum access opportunity of the SU

because of the increasing false alarm probability; however, improving detection performance needs to increase the sensing time, which decreases the data transmission time. Hence, we need to optimize the sensing parameters to maximize the spectrum efficiency. The SU can transmit data effectively only when the absence of the PU is detected accurately. The accurate idle detection probability of subchannel l is $P_r(\theta_l = 0) (1 - Q_f^l)$, and the transmission rate of SU n in subchannel l is given by $R_{n,l} = a_{n,l} \log \left(1 + \frac{p_{n,l} g_{n,l}^2}{\sigma_l^2} \right)$, where $a_{n,l} = \{0, 1\}$ denotes whether subchannel l is allocated to SU n , $p_{n,l}$ indicates the transmission power of the SU n in subchannel l , and $g_{n,l}$ denotes the subchannel gain between receiver and transmitter of SU n . Supposing the frame duration is T and the length of each cooperative interaction slot is ε , the overall spectrum efficiency of N SUs over L subchannels is given as follows:

$$\eta_{SE} = \frac{T - \tau - N\varepsilon}{T} \sum_{n=1}^N \sum_{l=1}^L \left[P_r(\theta_l = 0) (1 - Q_f^l) a_{n,l} \log \left(1 + \frac{p_{n,l} g_{n,l}^2}{\sigma_l^2} \right) \right] \quad (9)$$

Our goal is to maximize the spectrum efficiency of the SU by jointly optimizing sensing time, subchannel allocation, and transmission power, subject to the constraints that the detection probability is above the lower limit Q_d^{\min} , the total power of SU n is below the maximal power p_n^{\max} , and one subchannel is only allocated to one SU. Supposing the spectrum sensing power is p_c , the optimization problem of SEM is given as follows:

$$\max_{\tau, \{a_{n,l}\}, \{p_{n,l}\}} \eta_{SE} \quad (10a)$$

$$\text{s.t. } Q_d^l \geq Q_d^{\min}, l = 1, 2, \dots, L \quad (10b)$$

$$\sum_{l=1}^L a_{n,l} p_{n,l} + p_c \leq p_n^{\max}, n = 1, 2, \dots, N \quad (10c)$$

$$\sum_{n=1}^N a_{n,l} = 1, a_{n,l} = \{0, 1\}, l = 1, 2, \dots, L \quad (10d)$$

$$0 \leq \tau \leq T - N\varepsilon; \quad (10e)$$

$$p_{n,l} \geq 0, n = 1, 2, \dots, N, l = 1, 2, \dots, L \quad (10f)$$

For simplifying the optimization problem (10), we relax the integer $a_{n,l}$ with any value within $[0,1]$ and let $\omega_{n,l} =$

$a_{n,l} p_{n,l}$. Then, we have $R_{n,l} = a_{n,l} \log \left(1 + \frac{\omega_{n,l} g_{n,l}^2}{a_{n,l} \sigma_l^2} \right)$. From (8) and (9), η_{SE} improves with the decreasing of Q_f^l while Q_f^l reduces with the decreasing of Q_d^l . Hence, η_{SE} may reach the maximum only when $Q_d^l = Q_d^{\min}$. The optimization problem is rewritten as follows:

$$\max_{\tau, \{a_{n,l}\}, \{\omega_{n,l}\}} \eta_{SE} = \frac{T - \tau - N\varepsilon}{T} \sum_{n=1}^N \sum_{l=1}^L \left[P_r(\theta_l = 0) (1 - Q \left(\kappa + \bar{\gamma}_l \sqrt{N\tau f_s} \right)) R_{n,l} \right] \quad (11a)$$

$$\text{s.t. } \sum_{l=1}^L \omega_{n,l} \leq \hat{p}_n^{\max}, n = 1, 2, \dots, N \quad (11b)$$

$$\sum_{n=1}^N a_{n,l} = 1, a_{n,l} \in [0, 1], l = 1, 2, \dots, L \quad (11c)$$

$$0 \leq \tau \leq T - N\varepsilon \quad (11d)$$

$$\omega_{n,l} \geq 0, n = 1, 2, \dots, N, l = 1, 2, \dots, L \quad (11e)$$

where $\kappa = Q^{-1}(Q_d^{\min})(\bar{\gamma}_l + 1)$ and $\hat{p}_n^{\max} = p_n^{\max} - p_c$. Then, we will give the following theorem.

Theorem 1 *Problem (11) is a convex optimization problem.*

Proof We often let $Q_f^l \leq 0.5$ and then have $\kappa + \bar{\gamma}_l \sqrt{N\tau f_s} \geq 0$. Fixing $R_{n,l}$, We can get the secondary derivative of η_{SE} in τ as follows:

$$\begin{aligned} \frac{\partial^2 \eta_{SE}}{\partial^2 \tau} &= -\frac{P_r(\theta_l = 0) \sqrt{Nf_s}}{T \sqrt{2\pi} \tau} \sum_{n=1}^N \sum_{l=1}^L \\ &\times \left[\bar{\gamma}_l R_{n,l} \exp \left(-\frac{(\kappa + \bar{\gamma}_l \sqrt{N\tau f_s})^2}{2} \right) \right] \\ &- \frac{T - \tau - N\varepsilon}{4T\tau \sqrt{2\pi}} \times \sum_{n=1}^N \sum_{l=1}^L \\ &\times \left[P_r(\theta_l = 0) R_{n,l} \exp \left(-\frac{(\kappa + \bar{\gamma}_l \sqrt{N\tau f_s})^2}{2} \right) \right. \\ &\left. \times \left((\kappa + \bar{\gamma}_l \sqrt{N\tau f_s}) \bar{\gamma}_l^2 Nf_s + \bar{\gamma}_l \sqrt{Nf_s} \tau^{\frac{1}{2}} \right) \right] < 0 \end{aligned} \quad (12)$$

which indicates that η_{SE} is convex in τ . Moreover, $R_{n,l}$ is obviously convex in $(a_{n,l}, \omega_{n,l})$. Since η_{SE} is the non-

negative linear combination of $R_{n,l}$, η_{SE} is also convex in $(\{a_{n,l}\}, \{\omega_{n,l}\})$. Hence, η_{SE} is a convex optimization problem about $(\tau, \{a_{n,l}\}, \{\omega_{n,l}\})$. \square

We use the alternating direction optimization (ADO) to get the solution to the optimization problem. Firstly, fixing τ , we optimize $(a_{n,l}, \omega_{n,l})$. Using the Lagrange multiplier, the optimization function is given by

$$\begin{aligned} \Gamma(a_{n,l}, \omega_{n,l}) = & \sum_{n=1}^N \sum_{l=1}^L \left[\rho_l a_{n,l} \log \left(1 + \frac{\omega_{n,l} g_{n,l}^2}{a_{n,l} \sigma_l^2} \right) \right] \\ & - \sum_{n=1}^N \left[\mu_n \left(\sum_{l=1}^L \omega_{n,l} - \hat{p}_n^{\max} \right) \right] \\ & - \sum_{l=1}^L \left[\nu_l \left(\sum_{n=1}^N a_{n,l} - 1 \right) \right] \end{aligned} \quad (13)$$

where $\rho_l = P_r(\theta_l = 0) (1 - Q_l^f)$ is constant and μ_n for $n = 1, \dots, N$ and ν_l for $l = 1, \dots, L$ are the Lagrange multipliers. Through calculating $\frac{\partial \Gamma}{\partial a_{n,l}} = 0$ and $\frac{\partial \Gamma}{\partial \omega_{n,l}} = 0$, we have

$$\omega_{n,l} = \rho_l a_{n,l} \left[\frac{1}{\mu_n} - \frac{\sigma_l^2}{g_{n,l}^2} \right]^+ \quad (14)$$

$$a_{n,l} = \begin{cases} 0, & \nu_l \leq \Phi_{n,l}(\mu_n) \\ 1, & \nu_l > \Phi_{n,l}(\mu_n) \end{cases} \quad (15)$$

where $\Phi_{n,l}(\mu_n) = \rho_l \left(\log \left(\frac{g_{n,l}^2}{\mu_n \sigma_l^2} \right) + \frac{\mu_n \sigma_l^2}{g_{n,l}^2} - 1 \right)$. Then, the Lagrange multipliers μ_n and ν_l can be obtained by using the gradient method that leads to the following update equations

$$\begin{aligned} \mu_n(t+1) &= \left[\mu_n(t) + \zeta_1(t) \times \left(\sum_{l=1}^L \omega_{n,l} - \hat{p}_n^{\max} \right) \right] \\ \nu_l(t+1) &= \left[\nu_l(t) + \zeta_2(t) \times \left(\sum_{n=1}^N a_{n,l} - 1 \right) \right] \end{aligned} \quad (16)$$

where $t \geq 0$ is the iteration index and $\zeta_1(t)$ and $\zeta_2(t)$ are both the positive step sizes. Then, the updated Lagrange multipliers in (16) is used for updating the power allocation in (14). Secondly, we fix $R_{n,l}$ with the optimized $(a_{n,l}, \omega_{n,l})$. Using the Newton iteration method, we can get

the optimal τ through iteratively updating $\tau^{(k)}$ until it is convergent, as follows:

$$\tau^{(k+1)} = \tau^{(k)} - \frac{\frac{\partial \eta_{SE}}{\partial \tau^{(k)}}}{\frac{\partial^2 \eta_{SE}}{\partial^2 \tau^{(k)}}} \quad (17)$$

where $k \geq 0$ is the iteration index. As mentioned above, we use ADO to optimize $(a_{n,l}, \omega_{n,l})$ and τ alternatively until $a_{n,l}$, $\omega_{n,l}$, and τ are all convergent, as shown in Algorithm 1. Then, if $a_{n,l} = 0$, the transmission power $p_{n,l} = 0$; otherwise, $p_{n,l} = \frac{\omega_{n,l}}{a_{n,l}}$. Since η_{SE} is convex in τ , a and ω , η_{SE} is non-decreasing during each iteration, which is described as follows:

Algorithm 1 Joint optimization algorithm based on ADO

- 1: Initialize $k = 0$ and $\tau^{(k)}$ with any value within $[0, T - N\varepsilon]$, $\{a_{n,l}\}^{(k)} = \{0\}$ and $\{\omega_{n,l}\}^{(k)} = \{0\}$;
 - 2: **while** $\eta_{SE}(\tau^{(k)}, \{a_{n,l}\}^{(k)}, \{\omega_{n,l}\}^{(k)})$ is not convergent **do**
 - 3: With given $\tau^{(k)}$, obtain the Lagrange multiplier function (13);
 - 4: Set $t = 0$, $\{\mu_n(t)\}$, $\{\nu_l(t)\}$, $\zeta_1(t)$ and $\zeta_2(t)$ with the presettled values;
 - 5: **while** $\{\nu_l(t)\}$ and $\{\mu_n(t)\}$ are not convergent **do**
 - 6: Update $\{a_{n,l}\}^*$ and $\{\omega_{n,l}\}^*$ with $\{\mu_n(t)\}$ and $\{\nu_l(t)\}$ by (14) and (15);
 - 7: Update $\{\mu_n(t+1)\}$ and $\{\nu_l(t+1)\}$ with updated $\{a_{n,l}\}^*$ and $\{\omega_{n,l}\}^*$;
 - 8: Let $t = t + 1$;
 - 9: **end while**
 - 10: Set $\{a_{n,l}\}^{(k+1)} = \{a_{n,l}\}^*$ and $\{\omega_{n,l}\}^{(k+1)} = \{\omega_{n,l}\}^*$;
 - 11: With $\{a_{n,l}\}^{(k+1)}$ and $\{\omega_{n,l}\}^{(k+1)}$, calculate $\tau^{(k+1)}$ by (17);
 - 12: Let $k = k + 1$;
 - 13: **end while**
 - 14: : Output $\tau^{(k)}$, $\{a_{n,l}\}^{(k)}$ and $\{\omega_{n,l}\}^{(k)}$.
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$$\begin{aligned} \eta_{SE}(\tau^{(k)}, \{a_{n,l}\}^{(k)}, \{\omega_{n,l}\}^{(k)}) &\leq \eta_{SE}(\tau^{(k+1)}, \{a_{n,l}\}^{(k)}, \{\omega_{n,l}\}^{(k)}) \\ &\leq \eta_{SE}(\tau^{(k+1)}, \{a_{n,l}\}^{(k+1)}, \{\omega_{n,l}\}^{(k)}) \\ &\leq \eta_{SE}(\tau^{(k+1)}, \{a_{n,l}\}^{(k+1)}, \{\omega_{n,l}\}^{(k+1)}) \end{aligned} \quad (18)$$

Hence, the convergence of η_{SE} can be obtained after some iterations.

Supposing the estimation error is δ , η_{SE} will be convergent when $\tau^{(k)}$, $\{a_{n,l}\}^{(k)}$, and $\{\omega_{n,l}\}^{(k)}$ are all convergent. Thus, the iterative complexity of the joint optimization algorithm is given by $O\left(\frac{1}{\delta^3}\right)$.

2.4 Energy efficiency maximization (EEM)

Compared to the traditional communication system, the SU may consume more energy due to spectrum sensing power. Thus, we use energy efficiency to evaluate the energy consumption of cooperative spectrum sensing. We define the energy efficiency as spectrum efficiency to energy consumption ratio. The consumed total energy for spectrum sensing and data transmission within unit time is given by

$$E_T = \frac{1}{T} \left(Np_c(\tau + \varepsilon) + (T - \tau - N\varepsilon) \sum_{n=1}^N \sum_{l=1}^L [a_{n,l} p_{n,l}] \right) \quad (19)$$

Hence, the energy efficiency of cooperative spectrum sensing is given by

$$\eta_{EE} = \frac{\eta_{SE}}{E_T} = \frac{(T - \tau - N\varepsilon) \sum_{n=1}^N \sum_{l=1}^L \left[P_r(\theta_l = 0) (1 - Q_f^l) a_{n,l} \log \left(1 + \frac{p_{n,l} g_{n,l}^2}{\sigma_l^2} \right) \right]}{Np_c(\tau + \varepsilon) + (T - \tau - N\varepsilon) \sum_{n=1}^N \sum_{l=1}^L [a_{n,l} p_{n,l}]} \quad (20)$$

We seek to maximize η_{EE} by jointly optimizing $\{\tau, \{a_{n,l}\}, \{p_{n,l}\}\}$. The optimization problem of EEM is given by

$$\max_{\tau, \{a_{n,l}\}, \{p_{n,l}\}} \eta_{EE} \quad (21a)$$

$$\text{s.t. } Q_d^l \geq Q_d^{\min}, l = 1, 2, \dots, L \quad (21b)$$

$$\sum_{l=1}^L a_{n,l} p_{n,l} + p_c \leq p_n^{\max}, n = 1, 2, \dots, N \quad (21c)$$

$$\sum_{n=1}^N a_{n,l} = 1, a_{n,l} \in \{0, 1\}, l = 1, 2, \dots, L \quad (21d)$$

$$0 \leq \tau \leq T - N\varepsilon; \quad (21e)$$

$$p_{n,l} \geq 0, n = 1, 2, \dots, N, l = 1, 2, \dots, L \quad (21f)$$

We have proven $\eta_{SE}(\tau, \{a_{n,l}\}, \{p_{n,l}\})$ to be a continuous positive convex function. As $E_T(\tau, \{a_{n,l}\}, \{p_{n,l}\})$ is a linear positive function, we can solve the optimization problem (21) by the Dinkelbach optimization [14].

Setting $q = \frac{\eta_{SE}(\tau, \{a_{n,l}\}, \{p_{n,l}\})}{E_T(\tau, \{a_{n,l}\}, \{p_{n,l}\})}$, the optimization problem (21) can be rewritten as follows:

$$\max_{\tau, \{a_{n,l}\}, \{p_{n,l}\}, q} \eta_{SE}(\tau, \{a_{n,l}\}, \{p_{n,l}\}) - q E_T(\tau, \{a_{n,l}\}, \{p_{n,l}\}) \quad (22a)$$

$$\text{s.t. (21b) - (21f)} \quad (22b)$$

Supposing the feasible region of the solutions to (21) is denoted as S , the joint optimization algorithm based on the Dinkelbach optimization is described in Algorithm 2.

Algorithm 2 Joint optimization algorithm based on Dinkelbach's optimization

- 1: Initialize $q^{(k)} = 0$ where the iteration index $k = 1$, and the estimation error δ ;
 - 2: With given $q^{(k)}$, use the ADO to obtain the solution $(\tau^{(k)}, \{a_{n,l}\}^{(k)}, \{p_{n,l}\}^{(k)})$ to the following equivalent optimization problem:

$$F(q^{(k)}) = \max \left\{ \eta_{SE}(\tau, \{a_{n,l}\}, \{p_{n,l}\}) - q^{(k)} E_T(\tau, \{a_{n,l}\}, \{p_{n,l}\}) \mid (\tau, \{a_{n,l}\}, \{p_{n,l}\}) \in S \right\};$$
 - 3: If $F(q^{(k)}) \leq \delta$, go to step (5), otherwise, go to step (4);
 - 4: Let $q^{(k+1)} = \frac{\eta_{SE}(\tau^{(k)}, \{a_{n,l}\}^{(k)}, \{p_{n,l}\}^{(k)})}{E_T(\tau^{(k)}, \{a_{n,l}\}^{(k)}, \{p_{n,l}\}^{(k)})}$ and $k = k + 1$, then go to step (2);
 - 5: Output: the optimal solution $(\tau^{(k)}, \{a_{n,l}\}^{(k)}, \{p_{n,l}\}^{(k)})$.
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3 Simulations and discussions

In the simulations, the number of SUs is $N = 10$, the number of subchannels is $L = 32$, the channels obey the

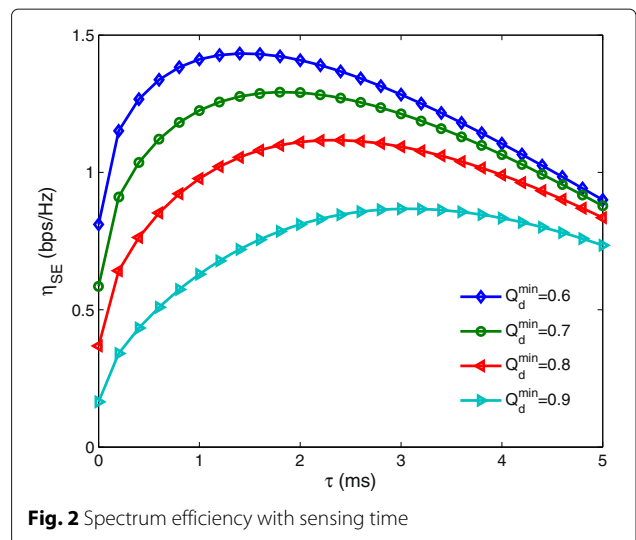


Fig. 2 Spectrum efficiency with sensing time

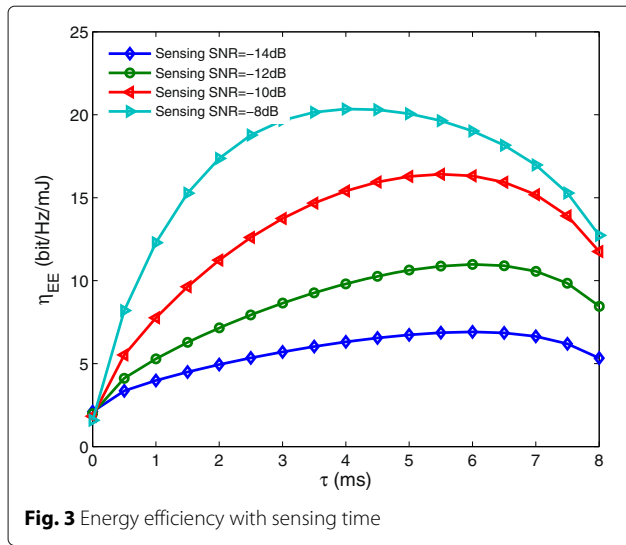


Fig. 3 Energy efficiency with sensing time

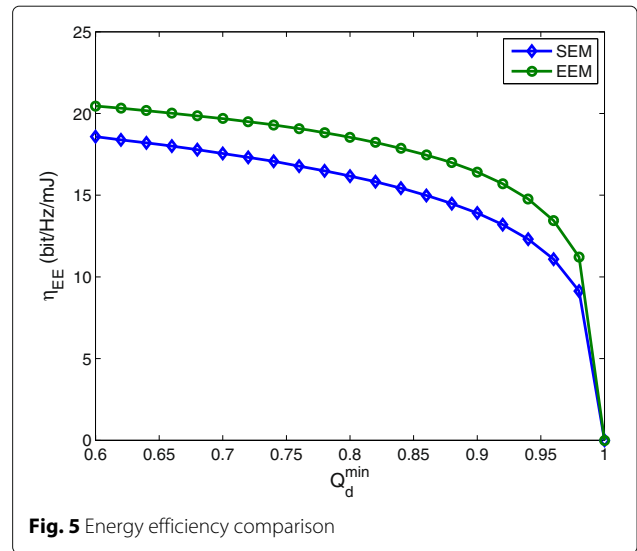


Fig. 5 Energy efficiency comparison

Rayleigh distribution with the mean -10 dB, the absence probability of the PU is $P_r(\theta_l = 0) = 0.5$, the frame duration is $T = 100$ ms, the length of cooperative interaction slot is $\varepsilon = 1$ ms, the sampling frequency is $f_s = 100$ KHz, the maximal power of each SU is $p_n^{\max} = 10$ mW, the sensing power $p_c = 1$ mW, and the noise power is $\sigma_l^2 = 0.01$ mW.

Figures 2 and 3 show spectrum efficiency η_{SE} and energy efficiency η_{EE} varying with sensing time τ , respectively. We can see that there exists an optimal τ to maximize η_{SE} or η_{EE} . When τ is smaller, the detection performance will degrade to decrease the spectrum access; however, when τ is larger, both transmission time and transmission energy will decrease. Thus, there is a tradeoff between spectrum sensing and data transmission. We also see that η_{SE} and η_{EE} improve as detection probability decreases

and sensing SNR increases. Figures 4 and 5 compare spectrum efficiency and energy efficiency of SEM and EEM, respectively. We can see that SEM can obtain higher spectrum efficiency while EEM may achieve higher energy efficiency, due to the different optimization objectives of SEM and EEM.

Then, we use power utilization ratio ρ to describe the usage of power in CSCN, which represents the power consumption required to accomplish the desired communication task when the maximum power is limited. ρ can be formulated as the ratio of the total consumed power to the total transmission power, as follows:

$$\rho = \frac{\sum_{n=1}^N \sum_{l=1}^L (a_{n,l} p_{n,l}) + N p_c}{\sum_{n=1}^N p_n^{\max}} \quad (23)$$

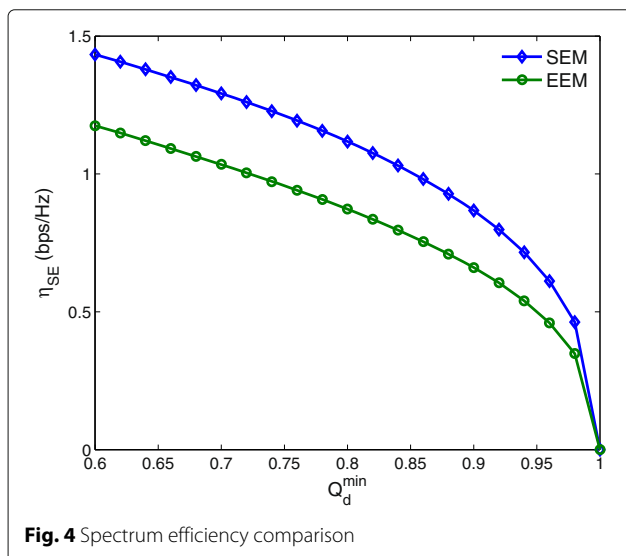


Fig. 4 Spectrum efficiency comparison

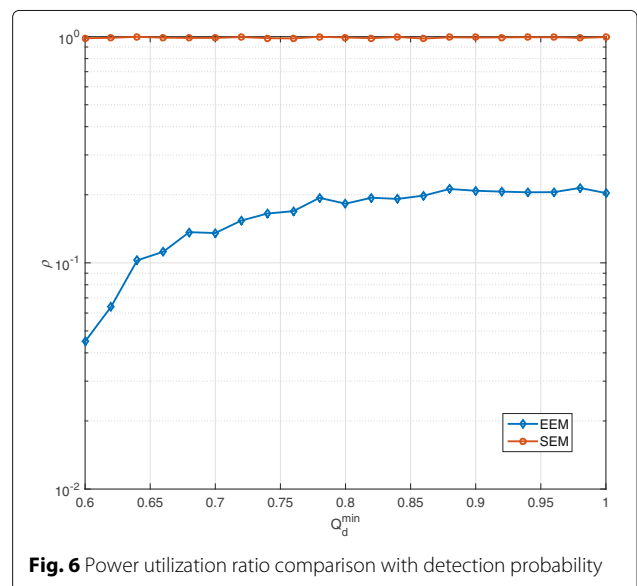


Fig. 6 Power utilization ratio comparison with detection probability

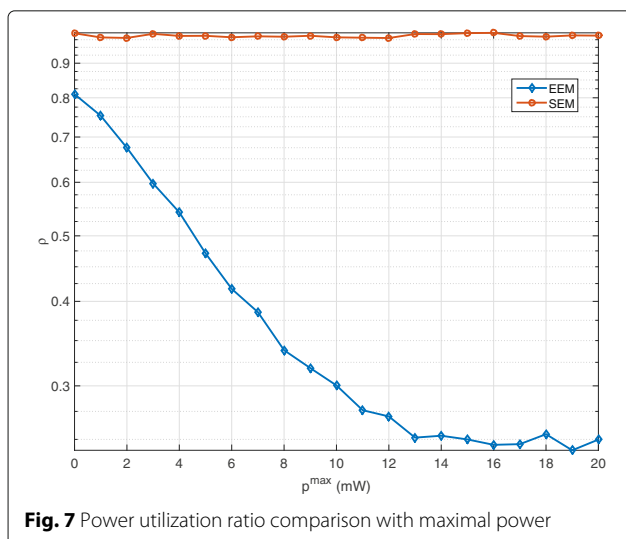


Figure 6 indicates the power utilization ratio comparison with detection probability. It can be seen that, as Q_d grows, the power utilization ratio of SEM is always 100%. SEM only focuses on maximizing spectrum efficiency and ignores the power consumption. Thus, it tends to use the entire power to maximize the spectrum efficiency during the optimization, leading to the 100% power utilization ratio. However, in EEM, the power consumption gains lots of attention and the power utilization ratio always keeps a low level, which indicates that detection performance is improved via setting a limit to the power consumption. Figure 7 shows the power utilization ratio comparison with maximal power. It is seen that EEM can also achieve higher power utilization compared with SEM.

4 Conclusions

In this paper, we have maximized spectrum efficiency and energy efficiency of periodic cooperative spectrum sensing for multichannel CSCN, respectively, through formulating optimization problems and jointly optimizing sensing time, subchannel allocation, and transmission power. We have got the following conclusions: (1) there is a tradeoff between spectrum sensing and data transmission; (2) SEM can obtain higher spectrum efficiency while EEM may achieve higher energy efficiency.

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Authors' contributions

XL conceived and designed the study. MJ performed the simulation experiments. XL wrote the paper. MJ reviewed and edited the manuscript. Both authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

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