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Power Optimization between Sensing and Signaling for Distributed Detection

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Abstract

The power of each sensor node in wireless sensor networks for signal detection applications is scarce and limited. Thus, the allocation of power resource of a node should make the detection performance of the whole network maximum, which is complex due to the detection probability of the whole system cannot be expressed explicitly. The ant colony optimization algorithm is good at solving multidimensional optimization problem. Consequently, continuous ant colony system (CACS) and ACO_R proposed in literature are adopted to optimize the allocation of node's power between sensing and communications. Simulation show that they can lead to a good power allocation. Meanwhile, the identical power allocation scheme (IPAS) that all sensor nodes have identical power assignment can achieve nearly the same detection performance as that achieved by the best scheme searched by CACS and ACO_R. As a result, particularly for a large number of identical sensors, IPAS can be employed to achieve nearly the best detection performance.

Keywords*: power allocation, signal detection, cross-layer optimization, wireless sensor network*

1. Introduction

Distributed detection (DD) systems with a set of geographically separated sensors have been investigated since 1980s. In the detection problem, one core objective of the system design is to distinguish between two hypotheses, such as the absence (Hypothesis 0) or presence (Hypothesis 1) of a certain target. Such detection ability is crucial for various applications. As an example, in a battlefield surveillance, the presence or absence of a target is usually determined before its attributes, such as its position or velocity, are estimated. With the development of wireless sensor networks (WSNs), many authors have analysed the performance of these DD systems in which transmissions from sensors to the fusion centre (FC) are subject to channel fading and noise [1-5], which may render the received decisions of sensors at the fusion centre unreliable. One prominent feature of a canonical WSN, however, is its limited node energy, which poses many challenges to network design and management.

The problem of optimizing detection performance with such imperfect communication brings a new challenge to distributed detection. Zhang et al. [6] considered the performance optimization with individual and total transmitter power constraints on the sensors. The power allocation scheme obtained strikes a trade-off between the communication channel quality and the local decision quality. Considering the scenario of using distributed radar-like sensors to detect the presence of an object through active sensing, Yang et al. [7] formulated the problem of energy-efficient routing for signal detection under the Neyman-Pearson criterion. Moreover, they proposed a distributed and energy-efficient framework that is scalable with respect to the network size, and is able to reduce greatly the dependence on the central fusion centre. Masazade et al. [8] evaluated the sensor thresholds of distributed signal detection system by formulating and solving a multiobjective optimization problem. Unfortunately, although the literature on energy-efficient communication or signal detection in WSNs is abundant, there is much less research on the power allocation between signal detection and communication, let alone the consideration of their joint optimization.

Obviously, the energy consumption of the whole system can be lowered by jointly optimizing the signal detection of sensor node and the signaling between sensor node and the FC. In another word, for a given node's power budget, we can find a power allocation scheme

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that strikes a trade-off between the communication channel quality and the detection quality of local sensors with the objective of the optimum detection performance at the FC. In general, there are many algorithms to solve the power allocation problem. However, the difficulty is that the probability of detection of a DD system cannot be expressed explicitly, especially with the problem in this paper.

In the 90s of 20th century, Italian scholar M. Dorigo put forward the ant colony optimization algorithm (ACO) [9]. Thereafter, ACO algorithms have been studied and utilized extensively. Artificial ants move randomly instead of deterministically. Therefore, it allows them to search wide variety of possible solutions of a problem independently and in parallel. In the same way, ACO based solutions are good at producing a good suboptimal solution in a very short period. These characteristics have inspired us to design a joint power assignment algorithm for distributed detection, with the objective of maximizing the overall probability of detection at the FC.

The remainder of this paper are organized as follows. In Section 2, the problem of distributed detection in parallel fusion networks with noisy channel, sensing model, link model, and fusion rule are formulated, respectively. The power allocation problem and its optimization by ACO solutions are given in Section 3 and Section 4, respectively. The numerical results are given in Section 5. Finally, Section 6 concludes the paper.

2. Problem Formulation

2.1. Distributed detection

Consider a scenario, where *N* sensors are scattered over an area to detect the presence (the signal plus noise Hypothesis H_1) or absence (the noise-only Hypothesis H_0) of an object, for example people, vehicles, or military targets, using radar-like sensors that emanate specific electromagnetic signals into the region of interest. For the active sensing application, the monitored space is typically divided into many range resolution cells. Each range cell could be probed sequentially in turn to determine the presence of a target by using radar pulses that are possibly launched by directional antennas. Assume the position of *k*-th sensor node is (x_k, y_k). Each sensor gathers information pertaining to a target in the position of (x_t, y_t) and makes a decision (for deciding the presence of the target and otherwise) and sends its binary decision to a fusion centre through an unreliable communication channel. In a word, the parallel fusion model is adopted. The position of fusion centre is assumed to be (x_{fc}, y_{fc}).

2.2. Sensing Model

According to the free-space radar equation, the power of the echoes from the target with RCS σ at range R_k to the radar can be expressed as:

$$P_r = P_t G^2 \lambda^2 \sigma (4\pi)^{-3} R_k^{-4} \tag{1}$$

where P_t is the radiated transmitted power, G is the gain of radar antenna, λ is the wavelength, and R_k is the range between the *k*-th radar and the target. For radar with noise figure F and bandwidth B, the output signal-to-noise ratio $(SNR)_o$ of its receiver is:

$$(SNR)_o = \tau P_t G^2 \lambda^2 \sigma \Big/ \left((4\pi)^3 kT_e BFLR_k^{\,4} \right) \tag{2}$$

Where *k* is Boltzmann's constant, T_e is the effective noise temperature, L is the system loss, τ is the pulse duration. The minimum detectable signal S_{min} and the minimum output signal-to-noise ratio $(SNR)_{o_{min}}$ of a radar receiver is related by:

$$S_{\min} = kT_e BF (SNR)_{o_{\min}} \tag{3}$$

The signal received by the k-th sensor is assumed to be:

$$y_k = \begin{cases} \sqrt{\tau P_r} + n_k & H_1 \\ n_k & H_0 \end{cases} \tag{4}$$

Assume that the k-th local sensor makes a binary decision $u_k \in \{+1, -1\}$, with false alarm rate $P_{lfk} = P[u_k = 1 | H_0]$ and detection probability $P_{ldk} = P[u_k = 1 | H_1]$, respectively. Therefore, the decision rule of the k-th sensor is:

$$u_k = \begin{cases} 1\ , & y_k \geq \tau_k \\ -1\ , & y_k < \tau_k \end{cases} \tag{5}$$

Where τ_k is decision threshold determined by the false alarm rate P_{lfk}. When n_k is Gaussian white noise with zero mean and variance σ_k^2, the return from the Swerling 0 target is constant. In this case, the P_{ldk} and P_{lfk} can be calculated as following,

$$P_{ldk} = \frac{1}{2}\mathrm{erfc}\left(\frac{\tau_k - \sqrt{\tau P_r}}{\sqrt{2\sigma_k^2}}\right), \quad P_{lfk} = \frac{1}{2}\mathrm{erfc}\left(\frac{\tau_k}{\sqrt{2\sigma_k^2}}\right) \ , \mathrm{erfc}(x) = \frac{2}{\sqrt{\pi}}\int_x^{+\infty} e^{-t^2}\,dt \tag{6}$$

2.3. Link Model

Let P_{tk}^{com} denote the radiated transmitted power of communication signal at the k-th sensor. Considering the path loss incurred during transmission, the power of signal received by the FC and from the k-th sensor is

$$P_{rk}^{fc} = P_{tk}^{com} \big/ (\varepsilon_k\, d_k^{\alpha_k}) \tag{7}$$

Where ε_k is a constant determined by the antenna characteristics, α_k is path loss exponent, and d_k is the range from the k-th sensor to the FC. Each local decision u_k is transmitted through a fading Rayleigh channel and the output of the channel for the k-th sensor is given by Equation (8).

$$r_k = \sqrt{P_{rk}^{fc}}\, h_k u_k + w_k \tag{8}$$

Where w_k is zero mean Gaussian noise with variance $\sigma_{w_k}^2$, and h_k is the gain of a real valued Rayleigh fading channel with the PDF given by $f(h_k) = 2h_k e^{-h_k^2}, h_k \geq 0$.

2.4. Fusion Rule

Based on the knowledge of channel statistics and local detection performance indexes, the LRT-CS (likelihood ratio test based on channel statistics) [1] can be reformulated as:

$$\Lambda_{tot} = \log\left[\frac{f(r_1, r_2, \cdots, r_N | H_1)}{f(r_1, r_2, \cdots, r_N | H_0)}\right] = \sum_{k=1}^{N} \log\left\{\frac{\sqrt{\frac{\pi P_{rk}^{fc}}{2}}\left[2P_{ldk} - 1 + \mathrm{erf}\left(\sqrt{\frac{P_{rk}^{fc}}{2}} a_k r_k\right)\right] r_k a_k \exp\left(\frac{P_{rk}^{fc}}{2} a_k^2 r_k^2\right) + 1}{\sqrt{\frac{\pi P_{rk}^{fc}}{2}}\left[2P_{lfk} - 1 + \mathrm{erf}\left(\sqrt{\frac{P_{rk}^{fc}}{2}} a_k r_k\right)\right] r_k a_k \exp\left(\frac{P_{rk}^{fc}}{2} a_k^2 r_k^2\right) + 1}\right\} \tag{9}$$

where $a_k = 1/\sqrt{\sigma_{w_k}^2\left(P_{rk}^{fc} + 2\sigma_{w_k}^2\right)}$ and $\mathrm{erf}(x) = \int_0^x \frac{2}{\sqrt{\pi}} e^{-t^2}\,dt$.

When using the fusion rule above, the global probability of false alarm P_{ftot} and the global probability of detection P_{dtot} are determined by Equation (10) and (11), respectively.

$$P_{ftot} = \mathrm{P}\left(\Lambda_{tot} > T \middle| \mathrm{H}_0\right) \quad (10)$$

$$P_{dtot} = \mathrm{P}\left(\Lambda_{tot} > T \middle| \mathrm{H}_1\right) \quad (11)$$

In the equations above, T is the detection threshold at the FC.

3. Optimization of Node's Power Allocation Schemes

3.1. Power Consumption of Sensor Node

In general, the power consumption of sensor node can be divided into two kinds, range-related power consumption and range-free power consumption. Here, consider two kinds of range-related power consumption. One is consumed by target sensing, denoted by P_k^{sensing}, and is related to the drain efficiency of power amplifier and antenna gains. Assuming the total energy efficiency is η_k^{sensing}, the consumed power $P_{ktot}^{\text{sensing}}$ and the radiated signal power P_k^{sensing} has the following relation.

$$P_{ktot}^{\text{sensing}} = P_k^{\text{sensing}} \left(\eta_k^{\text{sensing}}\right)^{-1} \quad (12)$$

For radar sensor, the larger the P_k^{sensing} is , the stronger the target's returns are and correspondingly the higher local sensor's detection capability. Therefore, sensor's target detection performance can be adjusted by adjusting P_k^{sensing}.

Another kind of range-related power consumption is that consumed by the communication between sensor node and the FC. Assuming that the power of the signal radiated into wireless channel by sensor k is denoted by P_k^{com} and total efficiency of power amplifier and antenna is denoted by η_k^{com}, then the power used for radiating signal P_{ktot}^{com} can be denoted by:

$$P_{ktot}^{com} = P_k^{com} \left(\eta_k^{com}\right)^{-1} \quad (13)$$

Except for the range-related power consumption, the other power consumption, for example from low noise amplifier, A/D converter, D/A converter and so on, is range-free. Furthermore, it can be considered fixed or cannot be controlled freely. Besides, for maintaining the normal function of sensor network, sensor node will consume some energy, which may fluctuate. Therefore, the power allocation of sensor node, considered in this paper, is a problem about how to share the adjustable power budget by the target sensing power $P_{\text{ktot}}^{\text{sensing}}$ and signaling power P_{ktot}^{com}. Assume that the total power budget is $P_{\text{k}}^{\text{sensing+com}}$ and then:

$$P_{\text{ktot}}^{\text{sensing}} + P_{ktot}^{com} \le P_{\text{k}}^{\text{sensing+com}} \quad (14)$$

For optimum system performance, the match between the communication capability and the detection performance index of local sensor node is needed. That is to say, the target sensing power $P_{\text{kopt}}^{\text{sensing}}$ and the signaling power $P_{\text{kopt}}^{\text{com}}$ maximize the detection capability of the whole system. At this time, there is:

$$P_{ktot}^{\text{sensing}} + P_{ktot}^{\text{com}} = P_k^{\text{sensing+com}} \quad (15)$$

3.2. Objective Function

For given admissible maximum false alarm rate α , the objective of system optimization is equivalent to finding the scheme of determining sensing power $P_{ktot}^{sensing}$ and communication power $P_{ktot}^{\text{com}} = P_{k}^{\text{sensing+com}} - P_{ktot}^{\text{sensing}}$, so as to maximize the global probability of detection P_{dtot}, expressed as the function of the decision threshold τ_k of *k*-th sensor, sensing power $P_{ktot}^{\text{sensing}}$, communication power P_{ktot}^{com} , and the decision threshold T at the FC, as shown in:

$$P_{dtot} \triangleq \Pr\left(\Lambda_{tot} \geq T \middle| \mathrm{H}_1\right) = P_D\left(\tau_1, P_{1tot}^{\text{sensing}}, P_{1tot}^{com} \cdots, \tau_k, P_{ktot}^{\text{sensing}}, P_{ktot}^{com} \cdots, T, P_{Ntot}^{\text{sensing}}, P_{ktot}^{com}\right). \tag{16}$$

The optimiztion problem can be expressed as:

$$\begin{aligned} &\max_{P_{1tot}^{\text{sensing}},\cdots,P_{ktot}^{\text{sensing}},\cdots,P_{Ntot}^{\text{sensing}}} P_{dtot} \\ &s.t. \quad \tau_k > 0, P_{ktot}^{\text{sensing}} > 0, P_{ktot}^{com} > 0,\ P_{ftot} \leq \alpha\ , P_{ktot}^{com} = P_{k}^{\text{sensing+com}} - P_{ktot}^{\text{sensing}} \end{aligned} \tag{17}$$

Where P_{ftot} is the global probability of false alarm.

4. Optimization Method

4.1. The Identical Power Allocation Scheme (IPAS)

In general, performance indexes (probabilities of false alarm and detection) of local sensor are not equal for the system with maximum detection performance. However, when the number of sensors approaches infinity, the system with identical local detectors will have asymptotic optimum performance [10]. Therefore, we assume that every sensor node has identical sensing and communication performance and their power supplies have identical power. Furthermore, assume the power budget that can be distributed between sensing and communication is $P_{\text{k}}^{\text{sensing+com}}$.

A simple method can be used to find a good allocation method. According to the total power budget $P_{\text{k}}^{\text{sensing+com}}$, determine a sufficient small power increase ΔP with the relation of $P_{\text{k}}^{\text{sensing+com}} = L\Delta P$. Let sensing power $P_{ktot}^{sensing}$ be ΔP , $2\Delta P$, $\cdots$, $L\Delta P$ successively and let communication power $P_{ktot}^{com} = P_{\text{k}}^{\text{sensing+com}} - P_{ktot}^{\text{sensing}}$. Next, compute P_{dtot} according to Equation (16). Record all the P_{dtot} s obtained and find the largest one among them. The sensing power $P_{ktot}^{sensing}$ with the largest P_{dtot} is the best one. In this method, all the nodes have the identical power allocation scheme. So, the method can be denoted by IPAS in abbreviation.

4.2. Ant Colony Optimization

Although ACO was proposed for combinatorial problems, researchers started to adapt it to continuous optimization problems. The simplest approach for applying ACO to continuous problems would be to discretize the real-valued domain of the variables. This approach has been successfully followed when applying ACO to the protein–ligand docking problem [11]. Recently, Socha and Dorigo [12] has proposed an ACO algorithms, named as ACO_R , that handle continuous parameters natively, where the probability density functions that are implicitly built by the pheromone model are explicitly represented by Gaussian kernel functions. Their approach has also been extended to mixed-variable problems [13].

Ants generally start out moving at random. However, when they encounter a previously laid trail, they can decide to follow it, thus reinforcing the trail with their own pheromone substance. This collective behaviour is a form of autocatalytic process. In this case, the more ants follow a trail; the more attractive that trail becomes to be followed by future ants. This process is thus expressed as a positive feedback loop, where the probability with which an ant select a path increases with the number of ants that previously selected the same path [2]. Hence, artificial ants probabilistically develop a solution iteratively by considering pheromone trails or/and local heuristic information as well.

Here, we adopt a model $Q=(S,\Omega,f)$ of continuous optimization problem, where S is a search space defined over a finite set of continuous decision variables; Ω is the set of constraints among the variables; $f:S\to\mathbb{R}$ is an objective function to be minimized. According to the statement above,

$$\begin{aligned}\mathbf{S}=\Big\{\mathbf{s}=\Big(\tau_1,P_{1tot}^{\text{sensing}},P_{1tot}^{\text{com}},\tau_2,P_{2tot}^{\text{sensing}},P_{2tot}^{com}\cdots,\tau_N,P_{Ntot}^{\text{sensing}},P_{Ntot}^{com},T\Big)\Big|\\ P_{ktot}^{\text{sensing}}\in\mathbb{R},P_{ktot}^{com}\in\mathbb{R},\tau_k\in\mathbb{R},T\in\mathbb{R},k=1,2,\cdots,N\Big\}\end{aligned} \tag{18}$$

$$f(\mathbf{s})=P_{dtot}=P_D\left(\tau_1,P_{1tot}^{\text{sensing}},P_{1tot}^{com}\cdots,\tau_k,P_{ktot}^{\text{sensing}},P_{ktot}^{com}\cdots,T,P_{Ntot}^{\text{sensing}},P_{ktot}^{com}\right) \tag{19}$$

The CACS algorithm was first proposed in [14]. It uses a continuous pheromone model consisting of a Gaussian pdf centred on the best solution found so far. The best solution at present is modified according to a weighted average of the distance between each individual in the population and the best solution found so far, as shown in Equation (20).

$$\sigma_j^2=\left(\sum_{k=1}^{N_{ant}}\frac{1}{\left|f_k-f_{opt}\right|}\right)^{-1}\sum_{k=1}^{N_{ant}}\frac{1}{\left|f_k-f_{\min}\right|}\left(s_k^j-s_{opt}^j\right) \tag{20}$$

Where N_{ant} is the number of ants defined in the algorithm, σ_j^2 is the variance of the *j*-th dimension, $\mathbf{s}_{opt}$ is the best solution at present and the superscript *j* denote the *j*-th dimension variable of the solution $\mathbf{s}$.

The main advantages of the CACS are that it requires the setting of just one parameter (the number of ants in the population) and presents a very simple mechanism to generate the ants of the next generation. On the other hand, a clear drawback is that it only investigates one promising region of the problem at a time, which means that the algorithm tends to concentrate the Gaussian pdf around local optima very quickly, thus leading to a premature convergence.

The ACO_R algorithm [12] consists of an archive that holds the k best solutions found so far. In conceptual terms, each solution corresponds to the centre of a different Gaussian pdf. Moreover, this archive is used to calculate the variance of each distribution, so that the whole process can be described as follows. Initially, the whole archive is stochastically created (using a uniform distribution), and the generated individuals are sorted in descending order of fitness. Then, the main iteration starts by first assigning a solution of the archive to each ant of the problem, with probability proportional to the weight ω_k of the *k*-th archive solution $\mathbf{s}_k$.

$$\omega_k=\frac{1}{qN_{ant}\sqrt{2\pi}}\exp\left(-\frac{(k-1)^2}{2q^2N_{ant}^2}\right) \tag{21}$$

Where N_{ant} is the number of ants, *k* is the rank of the solution on the archive, and *q* is a variable called locality of the search process and used to balance exploitation and exploration. The mean of each Gaussian is then defined as being the correspondent archive solution, and its variance is given by:

$$\sigma_l^i=\xi\sum_{k=1}^{N_{ant}}\frac{\left|s_k^i-s_l^i\right|}{N_{ant}-1},\ \ i=1,\cdots,N_{\dim} \tag{22}$$

Where ξ controls the speed of convergence to determine how fast the solutions of the archive will converge, s is a solution belonging to the archive, and $N_{\dim}$ is the dimension of the search space. Finally, this Gaussian distribution with mean and variance defined as described above is used to generate a new solution to the problem. After each ant has built a candidate solution, these candidate solutions are inserted into the archive and are sorted again. The algorithm then iteratively removes the worst solutions until the archive returns to its original size.

5. Numerical Simulation
5.1. Simulation Conditions
In our simulations, we use the WSN configuration described in Section 2. Consider a WSN with eight radar-like sensor nodes and a FC. All units of coordinate are meters. The FC is with coordinate (0,300). Assume that the Y-axis coordinates of all the sensors are zero and their X-axis coordinates are given in Table 1. Also, assume the target to be detected is with coordinate (20,-150).

Table 1. X-axis Coordinates of Sensor Nodes

Sensor's No.	1	2	3	4	5	6	7	8
X-axis coordinate	-180	-120	-60	0	60	100	160	220

Assume the false alarm rate α of the FC is 0.001. Each sensor has operating frequency 9375MHz, pulsewidth 10ns, and $\eta_{\mathrm{k}}^{\mathrm{sensing}}$=0.18. Assume a noise figure F = 8 dB, effective noise temperature $T_0 = 290K$, antenna gain $G = 28\mathrm{dB}$ and total receiver loss L = 4 dB. Also, assume that, for targets following the Swerling II fluctuations with average RCS of 5 m2, a probability of detection 0.5 and radar returns' power of -93dBm are required at maximum range of 150 meters with false alarm rate 0.01 or better. Assume that communication system operates at 2.4GHz and adopts the following path loss model given by Shellhammer [15].

$$pl(d) = \begin{cases} 40.2 + 20\log_{10}(d) & d \le 8m \\ 58.5 + 33\log_{10}\left(\frac{d}{8}\right) & d > 8m \end{cases} \quad (23)$$

Assume that the signal-to-noise loss of the practical communication receiver compared with the ideal one is 5dB. Also, assume that, for binary symmetric Rayleigh fading channel, a bit error rate 0.001 is required at receiver sensitivity of -95dBm at maximum range of 102 meters with transmitted power 5 dBm. Let the drain efficiency of power amplifier of communication module is 0.17.

Monte Carlo simulation is used to find the thresholds τ_k ($k = 1, 2, \cdots, N$) and T , as shown in the following. For positive integer n, generate I.I.D. samples x_1 , x_2 ,…, x_n , each with the same distribution as the random variable X . Sort x_1 , x_2 ,…, x_n in ascending order and denote them by $x_{(1)} \le x_{(2)} \le \cdots \le x_{(n)}$. Let $T = x_{(k)}$ and then the corresponding mean m_1 and standard deviation σ_1 of the false alarm rate of the detector are given in Equation (24) and Equation (25), respectively.

$$m_1 = \mathrm{E}\left(\Pr\left(X \ge x_{(k)}\right)\right) = \frac{n+1-k}{n+1} \quad (24)$$

$$\sigma_1 = \mathrm{std}\left(\Pr\left(X \ge x_{(k)}\right)\right) = \frac{1}{(n+1)}\sqrt{\frac{k(n+k-1)}{n+2}} \quad (25)$$

In the simulation of this paper, the parameters to estimate detection threshold are $n = 5\times10^{-7} - 1$ and $k = 5\times10^{7} - 50000$. Therefore, $m_1 = 0.001$ and $\sigma = 2.0\times10^{-4}$. The probability of detection was estimated by 3×10^{5} experiments.

5.2 Simulation results
When $P_k^{\mathrm{sensing+com}}$ =60mW and all the sensors have identical sensing power, the plot of probability of detection at FC versus sensing power are given in Figure 1. Obviously $P_{\mathrm{ktot}}^{\mathrm{sensing}} = 41.9$ mW will maximize the P_{dtot} . The maximum value obtained is 0.878. A bad power

allocation, for example $P_{\text{ktot}}^{\text{sensing}} = 5$ mW and P_{ktot}^{com} =55 mW, will make the system's detection performance less than 0.1. Therefore, a reasonable allocation of node's power is necessary.

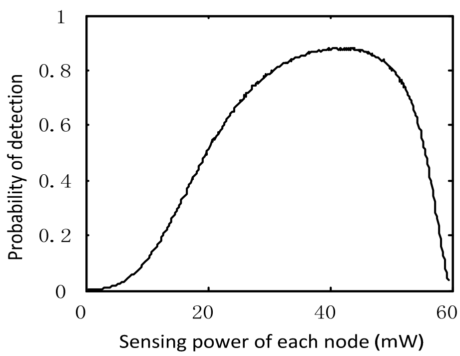

Figure 1. Probability of Detection versus Sensing Power under Power Budget of 60mW

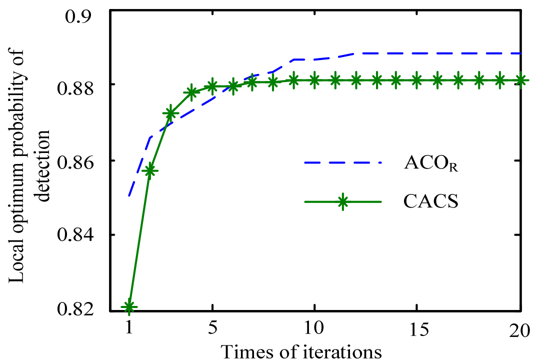

Figure 2. Local Optimum Probability Obtained during Iterations

Table 2. Power Allocation Scheme Obtained by ACO_R

	k	No. of iteration 1	2	3	4	5	6	7	8	9	10	11	12
$P_{ktot}^{\text{sensing}}$ (mw)	1	48.71	13.72	8.64	32.41	33.69	26.55	35.70	42.98	41.95	41.95	47.28	36.70
	2	53.22	37.40	43.22	56.07	44.51	46.65	42.05	45.00	44.38	44.38	45.30	45.61
	3	38.20	44.22	37.73	41.77	43.56	41.52	43.92	43.61	46.27	46.27	43.86	44.91
	4	28.94	39.51	33.73	35.25	34.62	36.71	37.93	37.42	37.73	37.73	37.90	37.65
	5	35.46	44.89	36.13	39.95	39.45	40.92	42.11	41.01	40.73	40.73	40.34	40.51
	6	46.21	49.	44.81	43.26	40.85	43.25	43.15	41.41	43.30	43.30	44.04	42.54
	7	31.75	37.66	40.48	39.97	44.28	38.77	42.96	42.30	44.41	44.41	45.17	44.94
	8	55.31	19.41	47.35	18.89	20.56	44.19	43.98	49.46	34.52	34.52	38.66	46.71
P_{dtot}		0.850	0.866	0.869	0.873	0.876	0.880	0.882	0.883	0.886	0.886	0.887	0.888

When using the ant colony optimization algorithm, the number of ants is assumed 100. The times of iterations are 20. The local best probability of detection of each iteration is given in Figure 2. The best sensing power of each sensor searched by ACOR at each iteration are given in Table 2. The results obtained by CACS are given in Table 3, where *k* stands for the No. of local sensor and $P_{ktot}^{\text{sensing}}$ is the sensing power of the *k*-th sensor.

Table 3. Power Allocation Scheme Obtained by CACS

	k	No. of iteration 1	2	3	4	5	6	7	8	9	10	11	12
$P_{ktot}^{\text{sensing}}$ (mw)	1	27.24	32.08	33.89	36.69	38.75	40.07	40.07	40.47	40.47	40.47	40.47	40.07
	2	34.54	35.67	39.25	43.89	48.17	48.92	48.92	50.24	50.24	50.24	50.24	48.92
	3	35.04	42.89	44.54	44.92	45.49	45.61	45.61	46.24	46.24	46.24	46.24	45.61
	4	36.62	40.09	41.30	42.70	42.91	43.16	43.16	43.42	43.42	43.42	43.42	43.16
	5	31.31	32.79	34.33	34.48	35.38	36.11	36.11	36.30	36.30	36.30	36.30	36.11
	6	28.42	35.32	41.63	44.32	44.79	44.97	44.97	45.66	45.66	45.66	45.66	44.97
	7	28.75	31.22	34.19	38.06	42.73	47.49	47.49	50.91	50.91	50.91	50.91	47.49
	8	32.42	34.01	38.24	38.64	41.92	42.26	42.26	44.13	44.13	44.13	44.13	42.26
P_{dtot}		0.850	0.821	0.857	0.872	0.878	0.880	0.880	0.880	0.881	0.881	0.881	0.881

From these results above, we can find that the CACS converges rapidly to the best solution. Moreover, the best solutions found by ACO_R outperform that by CACS slightly and there is a detection probability difference of 0.008. Compared with the best solution found by IPAS, both ACO_R and CACS can obtain better solutions. However, the detection probability difference between them is small and is not more than 0.01. Considering the simplicity and robustness of the IPAS, the IPAS is a feasible suboptimum optimization scheme for the WSN with identical nodes.

6. Conclusion

Considering the scenario of using distributed radar-like sensors to detect the presence of a target, we formulate the problem of power allocation between sensing and communication for signal detection under the Neyman-Pearson criterion. The power allocation scheme has been optimized by means of IPAS, CACS and ACO_R, respectively. Results show that they can lead to a good power allocation. Among them, the ACO_R can obtain the best solution and the CACS has the second best performance. Although the IPAS is the worst among them, it achieves nearly the same detection performance as compared with that achieved by CACS and ACO_R. Therefore, for the WSN with identical nodes, an identical power allocation scheme for all sensors can be employed to achieve nearly the best power allocation scheme.

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