[International Journal of Computer and Communication Technology](https://www.interscience.in/ijcct)

Volume 4 | Issue 1 Article 3

January 2013

Parallel energy-efficient coverage optimization using WSN with Image Compression

Jibanananda Mishra
DRIEMS, CUTTACK, jeevan_mishra2000@yahoo.co.in

Ranjan Kumar Jena
CET,BBSR,BPUT, ranjankjena@gmail.com

Rabinarayana Parida
SIT, BBSR, BPUT, rabiparida@rediffmail.com

Abinash Panda
DRIEMS, Cuttack, BPUT, abi_cul1@yahoo.co.in

Parallel energy-efficient coverage optimization using WSN with Image Compression

Jibanananda Mishra[1], *DRIEMS, Cuttack, BPUT*, jeevan_mishra2000@yahoo.co.in[1]
Ranjan kumar jena[2], *CET,BBSR,BPUT*, ranjankjena@gmail.com[2]
Rabinarayana Parida[3], *SIT, BBSR, BPUT*, rabiparida@rediffmail.com[3]
Abinash Panda[4], *DRIEMS, Cuttack, BPUT*, abi_cul1@yahoo.co.in[4]

Abstract: - Energy constraint is an important issue in wireless sensor networks. This paper proposes a distributed energy optimization method for target tracking applications. Sensor nodes are clustered by maximum entropy clustering. Then, the sensing field is divided for parallel sensor deployment optimization. For each cluster, the coverage and energy metrices are calculated by grid exclusion algorithm and Dijkstra's algorithm, respectively. Cluster heads perform parallel particle swarm optimization to maximize the coverage metric and minimize the energy metric. Particle filter is improved by combing the radial basis function network, which constructs the process model. Thus, the target position is predicted by the improved particle filter. Dynamic awakening and optimal sensing scheme are then discussed in dynamic energy management mechanism. A group of sensor nodes which are located in the vicinity of the target will be awakened up and have the opportunity to report their data. The selection of sensor node is optimized considering sensing accuracy and energy consumption. Experimental results verify that energy efficiency of wireless sensor network is enhanced by parallel particle swarm optimization, dynamic awakening approach, and sensor node selection.

Index Terms- Wireless sensor networks, power management, target tracking, collaborative sensing, optimization.

1. INTRODUCTION

Wireless sensor networks (WSNs) employ a large number of intelligent sensor nodes with sensing, processing, and wireless communicating capabilities to implement complicated tasks in the specified sensing field. Target tracking is a typical WSN application that calls for effective and efficient energy management. Taking into account energy optimization of sensor deployment and target tracking in WSN, we focus on parallel energy-efficient coverage optimization and dynamic energy management.

2. Dynamic Sensor Node Scheduling

With the predicted target position, potential scheduling approach can be implemented on the sensor nodes. For each sensing period, the sensor nodes that can detect the target in the next sensing period are determined. However, not all these sensor nodes have to be awakened and perform sensing task. A group of sensor nodes can be selected in advance properly considering both the sensing accuracy and energy consumption.

First, the semi major axis of error ellipse is taken as the metric of collaborative sensing error. It is assumed that sensing error should be less than A_0 in the target tracking application. Then, the group of sensor nodes gathers the acquired data and transmits them to a cluster head. A routing approach without much complexity is utilized here. Each sensor node signals with the same transmission power. The cluster head obtains the sequence of the distance to each sensor node by sorting the received signal power. The data are forwarded gradually approaching the cluster head. The nearest sensor node to the cluster head forwards the data along the lowest cost path. Assume that the coordinates of cluster head which has data compression task are denoted by $\left(x_0^{sen}, y_0^{sen}\right)$. For this cluster head, the coordinates of sensor nodes from near to far are $\left\{\left(x_i^{sen} y_i^{sen}\right) \mid i = 1,2,......,n_{sel}\right\}$ where n_{sel} is the number of sensor nodes with sensing task.

Therefore, the fitness function of different solution is

$$\text{Fitness} == \begin{cases} A + E_0, & A > A_{0,} \\ A_0 + E_s, & A \le A_{0,} \end{cases}$$

where A is the collaborative sensing error metric and E_0 is the upper bound of energy consumption E_s. It is assumed that there are n_c candidate sensor nodes. The optimization problem is to selecting a group of sensor nodes from the candidate sensor nodes. Here, we utilize a discrete binary particle swarm optimization (BPSO) to solve the sensor node selection problem.

For the particle $i, X_i^p = \left(x_{i,1}^p, x_{i,2}^p, ...x_{i,m}^p\right)$ represents current position. Binary coding scheme is used. If the sensor node j of the m candidate sensor nodes is used for sensing, then $x_{i,j}^p = 1;$ otherwise, $x_{i,j}^p = 0$

$$u_{i,j}^p(k+1) = \frac{1}{1+c^{-v_{i,j}(k+1)}},$$

$$x_{i,j}^p(k+1) = \begin{cases} 1, r < u_{i,j}^p(k+1), \\ 0, r \geq u_{i,j}^p(k+1), \end{cases}$$

Out of different selections of sensor nodes, the set of sensor nodes with the minimum value of Fitness is selected. In the next sensing period, the cluster head will awaken the selected sensor nodes and get all the available observations. Thus, the cluster head can compute the target position and send it to the sink node directly.

3. Simulation of Sensor Deployment Optimization

To balance the transmission energy consumption of cluster heads and cluster members, we set the cluster number c as 4. As shown in Fig. 1, all the stationary sensor nodes are partitioned into specified number of parts after the MEC approach performed by the sink node. We obtain the cluster centroids and boundary curves. The stationary sensor node number of the cluster is 38, 49, 34, and 39. Then, four mobile sensor nodes are placed at the cluster centroids and taken as the cluster heads.

Sensing field division method is applied to the WSN. Then, coverage efficiency of the clusters is evaluated. The mobile sensor node number for the four clusters is set as 19, 22, 14, and 21, respectively. The initial coverage state of the four clusters is shown inFig. 2. The area with darker gray levels means higher synthesis reliable detection probability. The area which does not belong to the related cluster is not considered.

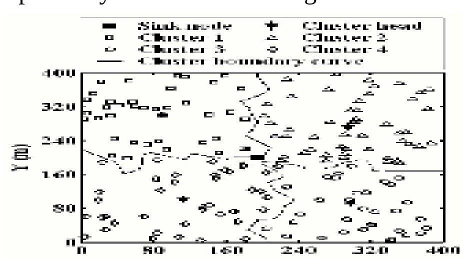

Fig. 1. Maximum entropy clustering results for WSN.

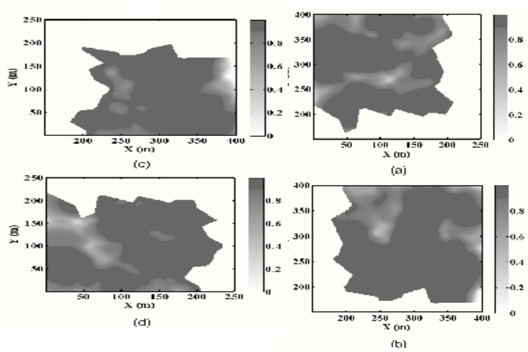

Fig. 2. The initial coverage state of the four clusters. (a) Cluster 1. (b) Cluster 2.(c) Cluster 3. (d) Cluster 4.

There is still some area which does not satisfied the synthesis reliable detection probability threshold R^{req} in each cluster, so PPSO is implemented on the cluster heads to optimize the positions of mobile sensor nodes. Adjusting the weight coefficient between coverage and energy metrics in each cluster, the impact of weight coefficient on optimal coverage state and energy consumption is analyzed in Fig. 3. For each cluster, we can find that the decreasing slope of energy metric is larger than that of coverage metric when increases. Thus, we can make trade-off between the coverage and energy metrics by setting the value of each cluster reasonably. The coverage-only situation is considered, where only the coverage metric is considered in sensor deployment. The performance of PPSO and PSO is compared in Fig. 4. No cluster is formed and the energy metric is defined by the lowest cost paths from sensor nodes to the sink node in PSO. In each single PSO process, the particle number is set as 20.

For PPSO, the convergence curves of coverage metrics in the four clusters can be acquired, while the convergence curve of total coverage ratio is calculated; for PSO, the convergence curves of WSN coverage ratio are presented. PPSO converges faster and has opportunity to obtain a much better WSN coverage ratio.

At first glance, the results shown in Fig. 4 may seem doubtful; it is unlikely to achieve better performance by a distributed algorithm than a centralized one. But this is true, and the reason is as follows: Here, optimization is achieved by a heuristic algorithm, where its performance is, to some extent, restricted by the computation complexity. To ensure real-time performance, many heuristic algorithms choose to set a maximum number of iterations as a stopping condition. Therefore, if the computation complexity is too high, the searching process of centralized algorithm will be easily stopped before global optimum is reached. However, distributed algorithm can easily reach the segmented optimums in each individual search space. Although the final results may be led into local optimum by simply fusing the segmented optimums, the enhanced exploration ability of distributed algorithm will compensate the drawbacks in global searching. In Fig. 4, the better performance of the distributed algorithm is obviously attributed to the small number of iterations. Then, we discuss the energy-efficient coverage optimization. Assume that the requirement of WSN coverage ratio for the application is 0.955. According to Fig. 3, we choose α =0.7, for cluster 1, α = 0.6 for cluster 2, α = 0.7 for cluster 3, and α = 0.8 for cluster 4. Fig. 5 shows coveragence curves of coverage and energy metrics. Besides, the total coverage ratio and average energy metric of the four clusters are given. The coverage and energy metric are both optimized, and they are adjusted to minimize objective function during iterations.

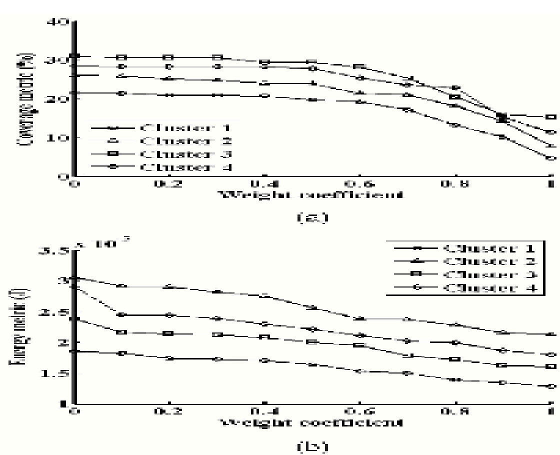

Fig. 3. The coverage and energy metrics with different weight coefficient in the four clusters : (a) Coverage ratio. (b) Energy metric.

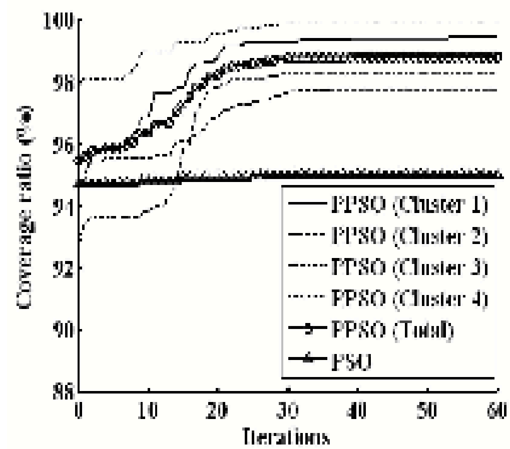

Fig. 4. The performance comparison of parallel particle swarm optimization and general particle swarm optimization.

Finally, the energy consumption of optimization results is evaluated. The deployment and communication paths are configured according to PPSO results. Mobile target is designed to move randomly in the sensing field for 300 s. All the sensor nodes around the target which are available for sensing will report its data. Then, the energy consumption curves of the four clusters during target tracking are presented in Fig. 6. We can see that the energy consumption of energy-efficient coverage situation is lower than that of coverage-only situation, especially in cluster 2, as its weight coefficient is larger than the other clusters. According to the results of Fig. 6, Table 1 presents the energy reduction of energy-efficient coverage situation, compared with the coverage-only situation. The relative reduction of energy consumption is calculated as :

$$\Delta = \frac{E_{WSN}^{1} - E_{WSN}^{2}}{E_{WSN}^{1}} \times 100\%$$

where E_{WSN}^{1} and E_{WSN}^{2} donate the energy consumption of WNS in the coverage–only and energy-efficient coverage situations, respectively. It can be seen that significant energy saving is achieved for each cluster. 26.82 percent for cluster 1, 16.03 percent for cluster, 2, 13.09 percent for cluster 3, and 26.37 percent for cluster 4. A total energy reduction of 20.48 percent can be obtained by the energy-efficient coverage optimization.

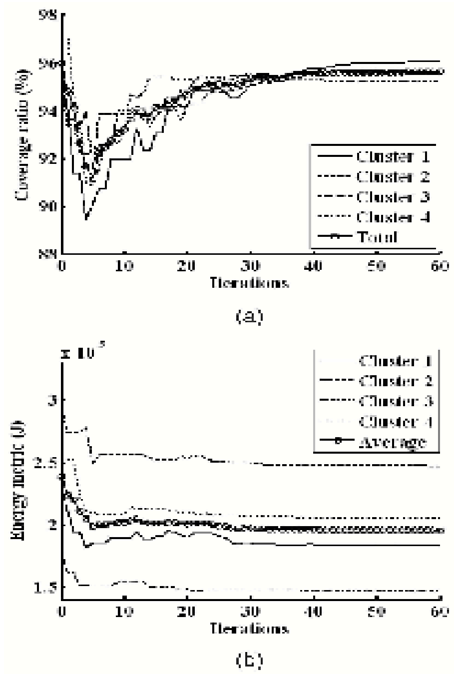

Fig : 5 Coverage curves of the coverage and energy metrics with energy metrics with energy-efficient coverage optimization. (a) Coverage ratio. (b) Energy metric,

4. Simulations of Dynamic Energy Management .

After the sensor deployment optimization, we take the results of energy-efficient coverage optimization for dynamic energy management. As shown in Fig. 7, the deployment of sensor nodes and the sink node are presented. The efficiency of PF-RBF prediction is then analyzed. Target position is predicted PF and PF-RBF. Utilizing the target trajectory in Fig. 7, the sink node performs the sensor node selection. The error of target position predicted by PF and PF-RBF is compared in Fig. 8.

It is guaranteed that the collaborative sensing error metric keeps below the sensing error threshold. However, the actual collaborative sensing error may be larger than the metric because of the prediction error, and it defines the observation error in the next sensing instant. Fig. 8 shows the prediction error in the x and y directions. PF-RBF produces much less error than PF does. That is, because PF always uses single-motion model, while PF-RBF performs prediction based on training of the observations.

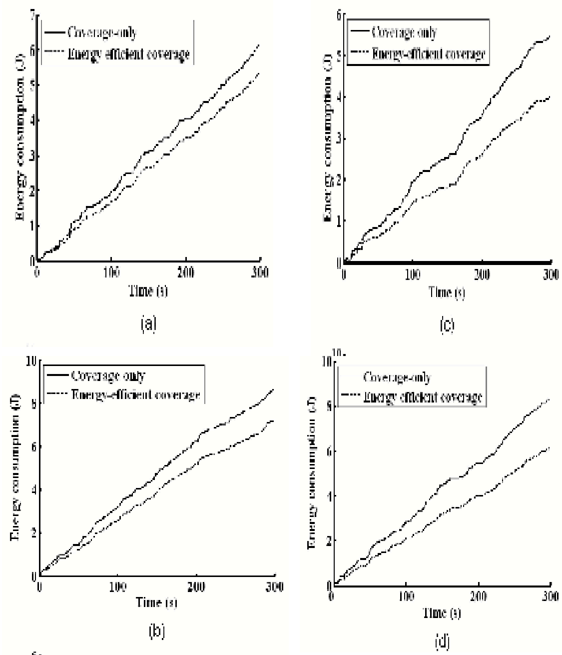

Fig. 6. Energy consumption curves for the situations of coverage-only and energy-efficient coverage in the four clusters during target tracking. (a) Cluster 1. (b) Cluster 2. (c)

Hence, PF-RBF is not impacted by the posterior distribution error of each particle and can obtain the robust prediction performance. Thereby, it can reduce the error in the idle time estimation and actual collaborative sensing.

TABLE – 1

WSN Energy Consumption in the Situations of Coverage-Only and Energy-Efficient Coverage

Region	Energy consumption (J)		Energy reduction
	Coverage-only	Energy-efficient coverage	
Cluster 1	5.471	4.005	26.80%
Cluster 2	8.614	7.233	16.03%
Cluster 3	6.145	5.340	13.09%
Cluster 4	8.340	6.141	26.37%
Total	28.57	22.72	20.48%

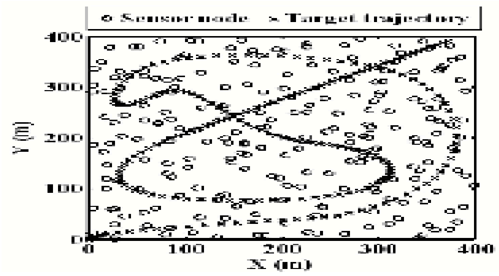

Fig. 7. Deployment of WSN and the designed target trajectory

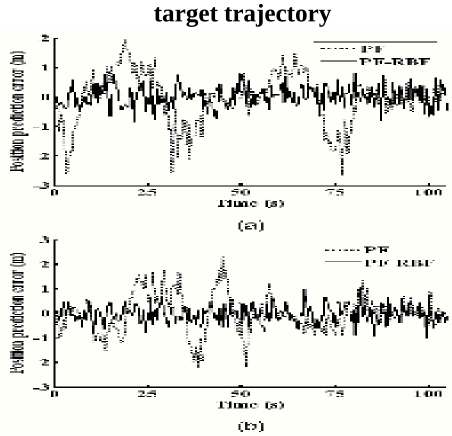

Fig. 8 . Prediction error of target position by PF and PF-RBF. (a) x direction. (b) y direction.

Finally, we analyze the efficiency of sensor node scheduling.

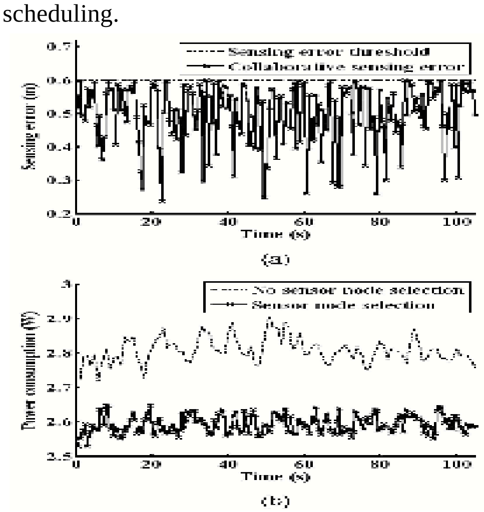

Fig. 9. Simulation results of target tracking with DPSO optimization. (a) Collaborative sensing error (b) Power consumption for target tracking.

Fig. 9 shows the simulation results of target tracking with DPSO optimization. In Fig. 9(a), the collaborative sensing error is less than the sensing error threshold during target tracking. Fig. 9(b) shows the entire power consumption for target tracking, If no sensor node selection is performed, all the sensor nodes in the vicinity of target will implement sensing task. Thus, sensor node selection acquires lower total energy consumption.

5. Conclusions

Focusing on the energy problems in the target tracking of WSN, this paper has proposed a parallel energy-efficient coverage optimization strategy and a PF-RBF prediction- based dynamic energy management. Based on sensor node clustering with MEC, WSN sensing field is divided to partition the entire coverage problem. Then, PPSO is implemented by cluster heads to maximize coverage area and minimize communication energy in each cluster. Trade- off between coverage rate and energy consumption can be accomplished during the sensor deployment optimization. During target tracking, the target position is predicted by PF-RBF, with the predicted target position at the next sensing instant, each sensor node estimates its idle time so that it can be sent to sleep and also wake up on time to be a sensing candidate. Thereby, sensor node selection is implemented to satisfy the sensing accuracy and minimize the energy consumption of target tracking. Experimental results verify that the proposed sensor deployment optimization strategy can enhance the energy efficiency of WSN coverage. Furthermore, PF-RBF achieves more robustness in motion prediction than PF does. Dynamic awakening and sensor node selection achieve energy saving in the target tracking application. In this paper, energy optimization is implemented for target tracking applications, involving sensor deployment in advance and sensing energy management.

References :

1. N.B. Karayiannis, "Maximum Entropy Clustering Algorithms and Their Application in Image Compression," Proc. 1994 IEEE Int'l Conf. Systems, Man, and Cybernetics, "Humans, Information, and Technology," vol. 1, pp. 337-342, 1994.

2. *J. Yao and M. Dash, "Entropy-Based Fuzzy Clustering and Modeling," Fuzzy Sets and Systems, vol. 3, pp. 282-188, Feb. 2000.*
3. *S. Meguerdichian and F. Koushanfar, "Coverage problems in Wireless Ad-Hoc Sensor Networks," Proc. IEEE INFOCOM, pp. 1380-1387, Mar. 2001.*
4. *L. Wang, H. Ji, and X. Gao, "Clustering Based on Possibilistic Entropy," Proc. Seventh Int'l Conf. Signal Processing, pp. 1467-1470, Mar. 2004.*
5. *G. Ciuprina, D. Ioan, and I. Munteanu, "Use of Intelligent-Particle Swarm Optimization in Elect romagnetics," IEEE Trans. Magnetics, vol. 38, no. 2, pp. 1037-1040, Mar. 2002.*
6. *X. Wang, S. Wang, and J. Ma, "An Improved Co-Evolutionary Particle Swarm Optimization for Wireless Sensor Networks with Dynamic Deployment Sensors," vol. 7, pp. 354-370, Mar. 2007.*
7. *X. Wang, J. Ma, S. Wang, and D. Bi, "Prediction-Based Dynamic Energy Management in Wireless Sensor Networks Sensors," vol. 7, pp. 251-266, Mar. 2007.*