Enhancing the Life Time of a Wireless Sensor Network in Target Tracking Applications

Phuong Pham and Sesh Commuri
School of Electrical and Computer Engineering, The University of Oklahoma, Norman, Oklahohoma, U.S.A.

Keywords: Wireless Sensor Networks, Target Tracking, Energy Efficiency, Kalman Filters.

Abstract: We propose a method to enhance the life span of the WSN under the constraint of tracking quality. The problem is cast as an optimization problem to minimize the power consumption cost function under the constraint of tracking quality. The cost function accounts for both the residual power of each sensor node and its sensing task. The cost function increases when the residual power of a sensor node decreases or a sensing task requires more power. The improvement in the tracking performance obtained by the proposed method is demonstrated through numerical examples.

1 INTRODUCTION

Target tracking is one of the important applications of a Wireless Sensor Network (WSN). Difficulties in the deployment of WSNs and the limited capabilities of each node restrict their long term utility for most applications. Some of the challenges that need to be addressed are the energy consumption, useful life, and quality of information obtained using these networks. These problems take on added importance in target tracking applications where the target is mobile and the sensor measurements are noisy.

Energy consumption and tracking quality (Demigha et al., 2012), (Zhao et al., 2002) are two main challenges in tracking of a dynamic target using WSNs. To save energy consumption, Fang and Li (Fang and Li, 2009) proposed a distributed estimation method for reducing communication and compressing data. Other approach (Cui et al., 2007) minimized quantization error and transmission power. Lin et al., 2009 investigated the energy-efficient multiple sensor scheduling, and calculated the optimal sampling time to meet the tracking performance. Several sensor activation schemes were used in (Pattem et al., 2003) to reduce power consumption under the effect of tracking quality. Information content-based sensor selection algorithm was proposed by (Onel et al., 2009). The optimization approaches (Masazade et al., 2012), (Mukherjee et al., 2011) were proposed to reduce overall power consumption of sensor networks. Smart scheduling methods (Atia et al., 2011), (Fuemmeler et al., 2011) were proposed to activate appropriate sensors for the tracking and to deactivate the "low-quality" sensors. The main purpose of these methods is to save the energy consumption and to prolong the network life time. Moreover, the tracking quality metrics, defined in these works, did not address the relationship between trilateration uncertainty and geometric distribution of sensor nodes.

To track a dynamic target using range-measurement sensors, the trilateration uncertainty is used as a main metric for tracking quality (Manolakis, 1996), (Yang and Liu, 2008), (Powers, 1966), (Thomas and Ros, 2005), (Fang, 1986), which depends on both the sensors' locations and the location of the target. Thus, a small number of sensor nodes can result in small tracking errors while a large number of nodes may result in poor tracking performance.

In this paper, we proposed a method to improve the life span of the WSN while maintaining the desired level of tracking quality. The problem is formulated as an optimization problem which minimizes the power consumption under the constraint of tracking quality. The power consumption cost depends on two parameters: the current residual power and the power expected to be consumed for a sensing mode. The cost is inversely proportional to the residual power of the node. Each sensor node operates in four modes (sleeping, active, sensing, and master mode) sorted as increasing

Pham P. and Commuri S..
Enhancing the Life Time of a Wireless Sensor Network in Target Tracking Applications.
DOI: 10.5220/0004432503730379
In *Proceedings of the 10th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2013), pages 373-379
ISBN: 978-989-8565-70-9

power consumption; a sleeping node consumes much less power than a master node does. By minimizing the power consumption cost under the constraint of trilateration uncertainty, the nodes with more residual power are scheduled for more power-intensive tasks, while the nodes with low battery power are scheduled to be in sleeping mode. The selection algorithm is suboptimal while the computational cost is significantly reduced. Moreover, the algorithm is implemented in a distributed manner, and is scalable to a network of a larger number of sensor nodes. The Kalman filter is proposed to further improve tracking quality. At a time instant, only one master node plays a role as the fusion center, which runs the Kalman filter and the selection algorithm. The mathematical analysis and numerical simulations will verify the effectiveness of the tracking algorithm.

2 PROBLEM FORMULATION

We consider the problem of target tracking using a wireless sensor network. A two-dimensional sensor field is densely deployed with stationary sensor nodes, which are equipped with transceivers, computational platforms, and range measurement units. When a target presents in the sensing field, the challenge is to schedule sensor operating modes (sleeping, active, sensing, or master mode) (1) to increase network life time and (2) to the required tracking quality. The proposed power consumption cost for using a specific sensor is a deceasing function with respect to its residual power. The optimization problem selects a set of sensor nodes that minimizes the power cost function under the constraint of trilateration uncertainty. The sensor selection algorithm also enables the distributed implementation of the tracking algorithm, i.e., Kalman filter.

2.1 Power Consumption Model and Cost Function

The power consumption cost function accounts for two conditions: the residual power of each node and its operating modes. To simplify the problems, it is assumed that each node has four operating modes (sorted as increasing power consumption) including: sleeping mode, active mode, sensing mode, and master mode. Moreover, the power consumption of each sensor in a particular operating mode is constant.

Let N be the total number of sensor nodes in the sensor field. Let $s = [s_1, s_2, \dots s_N]^T$, where s_i represents the operating mode of the i^{th} node, and $s_i \in \{0, 1, 2, 3\}$ (the values $0, 1, 2$ and 3 represent sleeping, active, sensing, and master mode, respectively).

Let the normalized residual power of a node be x (if $x = 0$, the node is depleted, while $x = 1$ the node has its full power). Let $p: [0, 1] \mapsto (0, \infty)$ be a continuous and decreasing function. Let p_i and $\mathscr{s}_i$ be normalized residual power and normalized power consumption, respectively, in one tracking interval. The power consumption cost for the i^{th} node is defined as

$$\mathcal{E}_i = \int_{p_i}^{p_i + \mathscr{s}_i} p(x)dx. \tag{1}$$

The total cost function of the network in one tracking interval is given as $\mathcal{E}_{total} = \sum_{i=1}^{N} \mathcal{E}_i$.

2.2 Rilateration Algorithm

The measurement model is given by the following equation

$$d_i = \|c_i - T_k\|_2 + \mu_i, \tag{2}$$

where $\|.\|_2$ is standard Euclidean norm; $c_i \in \mathbb{R}^2$ is the position of i^{th} sensor; $T_k \in \mathbb{R}^2$ is the position of the target; $d_i \in \mathbb{R}$ is the distance measurement; and $\mu_i \sim \mathcal{N}(0, \sigma_V^2)$ is the noise measurement.

Suppose that n_k sensors can sense the target, resulting in n_k nonlinear measurement equations (2). For each pair of integers (i, j), $1 \le i \ne j \le n_k$, the i^{th} and j^{th} in (2) are squared and subtracted to represent the measurement in the linear form. The location of the target T_k, the least square trilateration algorithm, is given by

$$T_k = (A_k^T A_k)^{-1} A_k^T r_k. \tag{3}$$

where $A_k \in \mathbb{R}^{M \times 2}$, $M = \frac{n_k(n_k-1)}{2}$, and $r_k \in \mathbb{R}^{M \times 1}$. $A_k = [A_{k_1} A_{k_2} \dots A_{k_M}]^T$ and $r_k = [r_{k_1} r_{k_2} \dots r_{k_M}]^T$.

$$A_{k_t} = 2(c_i - c_j),$$

$$r_{k_t} = (d_i - \mu_i)^2 - (\|c_i\|_2 - (d_j - \mu_j)^2 + \|c_j\|_2)$$

where $t = \varphi(i, j)$. The map $\varphi: [1 \div n_k] \times [1 \div n_k] \mapsto [1 \div M]$ is one-to-one.

The tracking system is given by the following two equations.

$$x_{k+1} = F_k x_k + w_k. \tag{4}$$

$$y_k = H_k x_k + \theta_k. \tag{5}$$

Where $x_k \in \mathbb{R}^4$ is the state of the target (location and velocity), $w_k \sim \mathcal{N}(0, Q_k)$: the process noise with covariance matrix Q_k. $y_k \in \mathbb{R}^2$ is location of the target calculated by trilateration algorithm (3). $\theta_k \in \mathbb{R}^2$ is the uncertainty of trilateration algorithm with the covariance matrix $\Theta_k \in \mathbb{R}^{2\times 2}$.

$$F_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \Delta t & 0 & 1 & 0 \\ 0 & \Delta t & 0 & 1 \end{bmatrix} \text{ and } H_k = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

where Δt is the tracking interval.

2.3 Power Saving Optimization Problem

Let $\mathcal{P}$ be the power set of all the possible combination of of all the nodes' operating modes. The size of $\mathcal{P}$ is 4^N.

Let $\mathscr{t}: \mathcal{P} \mapsto \mathbb{R}$ be a trilateration quality set function such that

$$\mathscr{t}(s) = \mathrm{Trace}(\Theta_k). \tag{6}$$

Where Θ_k is the uncertainty of the trilateration algorithm when the set of sensor nodes s is used for sensing.

Let $\mathscr{p}: \mathcal{P} \mapsto \mathbb{R}$ be the total power consumption cost function of the network. Thus,

$$\mathscr{p}(s) = \sum_i^N \int_{p_i}^{p_i + s_i} p(x)dx \tag{7}$$

Given a predefined bound on uncertainty error B, the optimization problem is:

$$\begin{gathered} \text{minimize } \mathscr{p}(s) \\ \text{subject to } \mathscr{t}(s) < B \end{gathered} \tag{8}$$

To solve this problem we divide it into three small problems: selection of the master node, and selection of sensing nodes, and finally selection of the active nodes.

3 ALGORITHMS AND ANALYSIS

In this section, the algorithm for selecting the master node, and sensing nodes are discussed. Since only sensing nodes affect the performance of the trilateration algorithm (i.e., matrix Θ_k), the master node, and sensing nodes can be selected independently in terms of trilateration quality function $\mathscr{t}(s)$ in (6).

3.1 Selection of Master Nodes

During each tracking interval, the master node transmits a broadcast message, receives data messages from the nodes within the measurement range of the target, and computes the Kalman filter. The master node consumes more power than other nodes; hence, the node with more residual power is preferred. On the other hand, the master node should be in the heading of the target so that the hand-over process can be kept less frequent. The choice of the master node does not affect the choice of the sensing nodes in terms of tracking performance, but it has an effect on the total power consumption cost function.

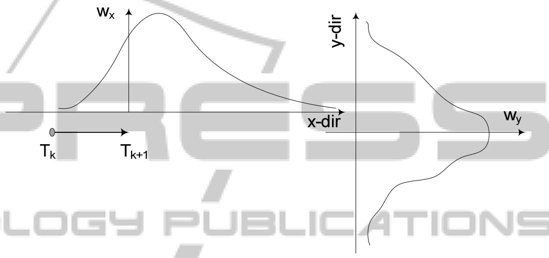

Figure 1: Distribution functions of the master node. The distribution of the cost function in the heading of the target should be the heavy tailed, and distributed of the cost function in the y-direction should be bell shape.

Suppose that the current location of the target at time k is T_k and the estimated position of the target at time $k+1$ is T_{k+1}. In Figure 1, the heading of the target $\overrightarrow{T_k T_{k+1}}$ is coincident with the x-direction. The distribution function for selecting the master node is given as

$$w_{master} = w_x w_y. \tag{9}$$

Where w_x and w_y, the bell shapes as shown in Figure 1, are distribution of the master node in x and y directions, respectively. The best candidate to be the master node maximizes w_{master}.

Let ρ_x be the sum of normalized power consumption cost a node and the cost for transmitting data to the network sink. The weighted cost function of the node for being the master node is

$$W = \alpha \rho_x + \beta w_{master}. \tag{10}$$

Where α and β are constants, and $\alpha + \beta = 1$.

3.2 Scheduling and Selection Algorithm

After selecting the master node, the following algorithm will schedule a set of sensing nodes that minimize the power consumption cost function.

The inputs of the algorithm are: n_k sensor nodes $\mathcal{S}_n = [S_1, S_2, \ldots, S_{n_k}]$, the target coordinate T, their residual power p_i for $i = 1 \div n_k$, and range measurement d_i for $i = 1{:}\, n_k$. The output is a set of selected sensors $[S^1, S^2, S^3] \subseteq \mathcal{S}_n$.

The main idea of the algorithm uses heuristic ranking system to sort nodes according to their power consumption costs. The suboptimal approach (1) eliminates the closed to collinear nodes and (2) minimize the total indices of the sorted costs. Instead of minimizing the total cost $\mathcal{E}_{total} = \sum_{i=1}^{3} \mathcal{E}_i$, the algorithm minimizes their sum of indices $i + j + k$.

Step 1: Calculate the power cost of each sensor node based on equation (1) $\mathcal{E}_i = \int_{p_i}^{p_i + \mathscr{s}_2} p(x)dx$ ($\mathscr{s}_2$ represents the sensing task), and sort the cost such that $\mathcal{E}_1 \le \mathcal{E}_2 \le \ \ldots \ \le \ \mathcal{E}_{n_k}$.

Step 2: Eliminate collinear nodes. If two or more sensor nodes together with the target are collinear or closed to collinear, all the nodes are eliminated from the selection pool except two nodes with highest residual power. After the collinear elimination process, no set of three collinear sensor nodes exists. Thus, 'low-quality' (resulting in large trilateration uncertainty) nodes are eliminated.

Step 3: Search for three best nodes that minimized the power consumption cost.

For each set $(i, j, k),\ 1 \le i, j, k \ \le n_k$.

- **Calculate** $\mathscr{t}(s)$ by (6) for nodes, $s = [S_i, S_j, S_k]$, if $\mathscr{t}(s) \le B$ (B is predefined trilateration uncertainty).
- **Choose** (i, j, k) such that $\mathscr{p}(s)$ in (7) is minimized.

Theorem 1: The heuristic search algorithm (Step 3 above) yields the optimal solution.

Proof: Let set $s = [S_i, S_j, S_k]$ be a solution of the algorithm and $Sm = i + j + k$. Clearly,

$$\mathcal{E}^0 = \min_{Sm=i+j+k} \mathscr{p}(s) = \min_{Sm=i+j+k} \ \mathcal{E}_{total} \qquad (11)$$

Let $s' = [S_{i'}, S_{j'}, S_{k'}]$ be another solution of the problem (4).

Obliviously, $i' + j' + k' \ge Sm$ due to the stop condition of the algorithm. There exists a set $[i^o, j^o,\ k^0]$ such that

$$\begin{cases} i' \ge \ i^0 \\ j' \ge \ j^0 \\ k' \ge \ k^0 \\ i^o + j^o + \ k^0 = Sm \end{cases}$$

Hence, $\mathcal{E}_{i'} \ge \mathcal{E}_{i^0}$, $\mathcal{E}_{j'} \ge \mathcal{E}_{j^0}$, and $\mathcal{E}_{k'} \ge \mathcal{E}_{k^0}$ and by (7)

$\mathscr{p}(s') = \mathscr{p}([S_{i'}, S_{j'}, S_{k'}]) \ge \mathscr{p}([S_{i^0}, S_{j^0}, S_{k^0}]) \ge \mathscr{p}(s) = \mathcal{E}^0$.

Thus, set s is the optimal solution for the Step 3. ■

Theorem 2: The solution for the optimization problem in (8) is suboptimal solution.

By Theorem 1, the solution in Step 3 is optimal. Thus, the solution of (8) is suboptimal due to the collinear elimination process in Step 2.

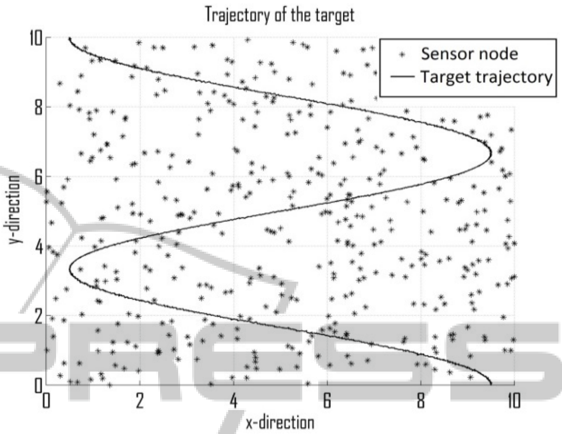

Figure 2: Trajectory of the target and distribution of the sensor nodes.

4 NUMERICAL EXAMPLE

The following example used a sensor field of dimensions 10×10 units to demonstrate the selection of a minimum number of sensor nodes and implementation of distributed Kalman filter for target tracking. Assume that 441 sensor nodes are randomly deployed in this sensor field as shown in Figure 2. The power consumption profile using in the simulation was based on the analysis in (Watfa and Commuri, 2006) even though our approach did not depend on any specific hardware platform. Let P_{Tx}, P_{Rx}, P_{Active}, P_{Sens}, P_{Sleep}, and P_{Comp} be the transmitting power, receiving power, active power, sensing power, sleeping power, and computational power respectively. Let P_{Max} be the maximum available power of a node. The normalized power consumption in each operating mode is defined as follows.

- Sleeping mode: $\mathscr{s}_0 = P_{Sleep}/P_{Max}$.
- Active mode: $\mathscr{s}_1 = (P_{Rx} + P_{Active})/P_{Max}$.
- Sensing mode: $\mathscr{s}_2 = (P_{Rx} + P_{Sens} + P_{Tx} + P_{Active})/\ P_{Max}$.
- Master mode $\mathscr{s}_3 = (P_{Tx} +\ nP_{Rx} + P_{Comp} + P_{Active})/P_{Max}$ where n is the number of sensing nodes.

Let the measurement noise variance σ_V=*0.1*, and the state noise variance $\sigma_S = 0.005$. Let the trilateration constraint in equation (8) be $B = 5\sigma_V$. The function $p(x)$ in (1) was chosen as $p(x) = \frac{1}{x+0.01}$ based on power management strategy.

The target was assumed to move along a sinusoid trajectory as shown in Figure 3. The sensing radius was 1.4, and the simulation time was 10 seconds

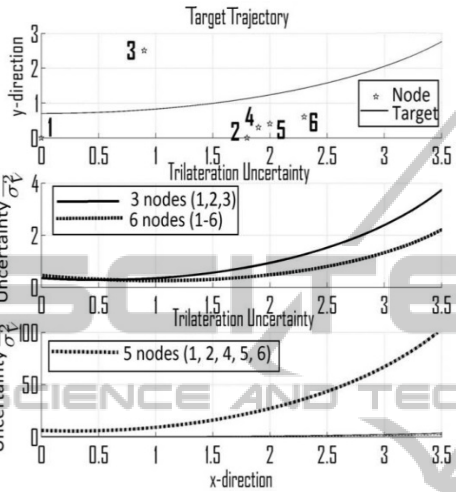

Figure 3: Uncertainty of trilateration algorithm. Coordinates of 6 sensor nodes from #1 to #6 are (0, 0), (1.8, 0), (0.9, 2.5), (1.9, 0.3), (2.0, 0.4) and (2.3, 0.6) relatively.

Figure 3 demonstrated the relationship between uncertainty of trilateration algorithm and the spatial distribution of sensor nodes. When all 6 nodes were chosen, the uncertainty of trilateration was the smallest. When 3 nodes (1, 2, 3) were chosen, the uncertainty was bigger but still met the requirement (smaller than $B = 5\sigma_V$). However, 5 nodes (1, 2, 4, 5, 6) yielded a large trilateration uncertainty, and did not meet the required tracking quality. Thus, to improve the tracking quality and to reduce number of active sensors, nodes at location (1, 2, 3) are preferable.

The selection algorithm was shown in Figure 4. The target were at (4.3, 6.2), and the sensing radius was 2.0. Initially, 20 nodes within the sensing range of the target were assumed to have uniformly random residual power.

Figure 5 illustrates the overall tracking performance along the x-direction, and the performance was improved by using the Kalman filter. The estimated error was initially high due to large initial error (the true coordinates of the target was at 9.5 in x-direction, but the initial value for the filter was 8.0), but it reduced greatly after about 0.3 second. The tracking performance (in black solid line) of three nodes (which resulted in minimum

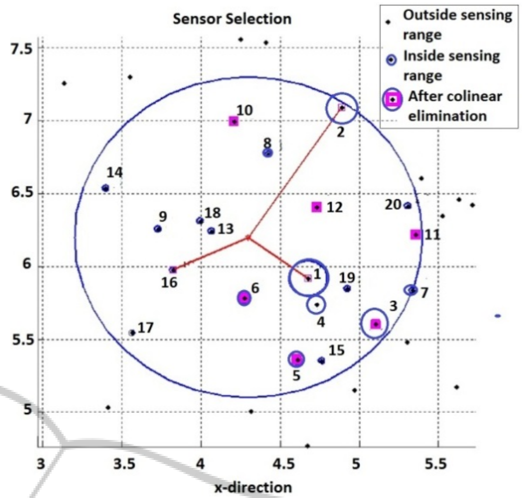

Figure 4: The sensor nodes represent by the dots. Radiuses of small circles are proportional to the residual power of sensor nodes. The squares represent the small group of sensors left after running the collinear elimination process. The sensors inside the big circle are able to sense the target. Three sensors #1, #2, and #16 minimized the power cost while still satisfying the required trilateration uncertainty. Meanwhile, three sensors #1, #2, #3 yielded the minimum power consumption cost, but did not meet the trilateration uncertainty condition.

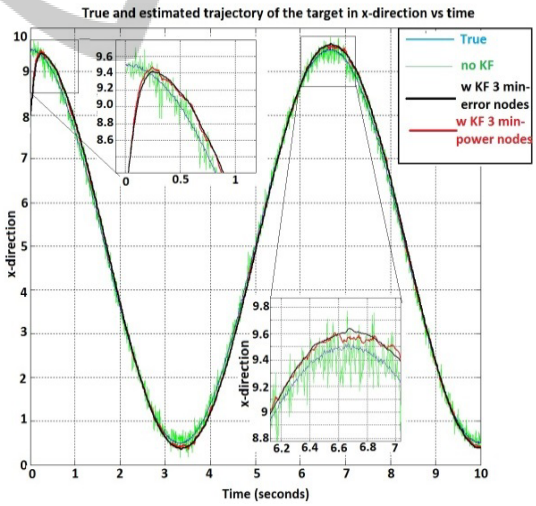

Figure 5: True and estimated trajectory of the target in x-direction. Without using the Kalman filter, the tracking error was high and fluctuated as shown in green line. When the Kalman filters were used (black and red line), the tracking errors were reduced. The red line was the performance when three nodes (which minimized power cost) were used. When three nodes (which minimized trilateration uncertainty) were used for tracking (black line), the tracking error is smaller and smother.

trilateration uncertainty) was better the performance of three nodes (red line) – which resulted in minimum power consumption cost. However, as shown in the Figure 5, the difference was not significant.

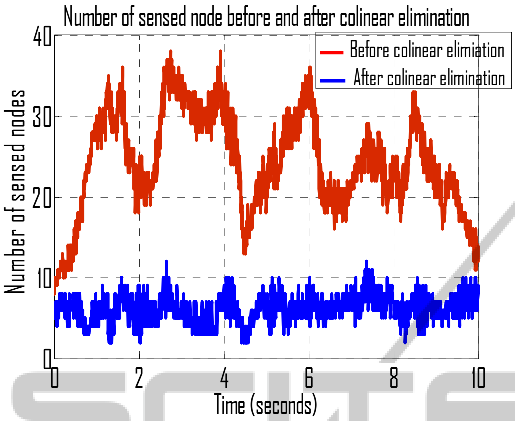

Figure 6: Number of sensed nodes before and after collinear elimination.

In Figure 6, the average number of sensed nodes before collinear elimination was 24.3, which resulted in 2,529 exhaustive search attempts. After collinear elimination process, only average 6.1 sensed nodes remained, which the average total search attempts reduced to 27.9 while the average actual search attempts were 19.5.

5 DISCUSSION

5.1 Selection of the Power Cost Function

In equation (1), power profile function $p(x)$ is a decreasing continuous function and is selected by the characteristic of a specific type of sensors and the power management strategy. Different candidate of $p(x)$ can result in different set of chosen sensor nodes, but nodes with more residual power are still preferable over nodes that power is almost depleted. Hence, the life time of the sensor network is improved.

5.2 Selection of the Master Node

In equation (10), if α is large, the weighted cost depends more on the current residual power of the sensor and its cost to transmit data to the network sink. If $\alpha = 1$, (or $\beta = 0$) the node with lowest power consumption cost is selected, but it can be outside the communication range of the target's sensed nodes in the next tracking interval. On the other hand, if $\alpha = 0$ (or $\beta = 1$), the selected master node is in the heading of the target, but its residual power may be almost depleted.

5.3 The Selection Algorithm

In worst case scenario, the calculation time of the selection algorithm is equal to that of exhaustive search. However, the proposed algorithm performs better in practice.

6 CONCLUSIONS

In this paper, an algorithm was proposed to enhance the life time of a WSN by solving an optimization problem which minimized the power consumption cost function under the constraint of tracking quality. Simulation illustrated that the suboptimal solution reduced both computational complexity and the number of active sensor nodes. Nodes with more residual power were preferred for power intensive tasks while nodes with low residual power were scheduled to sleep. The numerical examples show that the validity of the proposed approach. The future work will focus on the tracking problem in three-dimensional coordinate system with rigorous mathematical analysis.

ACKNOWLEDGEMENTS

The first author would like to thank Dr. Choon Yik Tang for the discussion about optimization problems and heuristic search.

REFERENCES

Atia, G. K., Veeravalli, V. V. & Fuemmeler, J. A. 2011. Sensor Scheduling For Energy-Efficient Target Tracking In Sensor Networks. *Ieee Transaction On Signal Processing,* 59, 4923 - 4937

Cui, S., Xiao, J.-J., Goldsmith, A., Luo, Z.-Q. & Poor, V. 2007. Estimation Diversity And Energy Efficiency In Distributed Sensing *Ieee Transaction On Signal Processing,* 55, 4683 - 4695

Demigha, O., Hidouci, W. & Ahmed, T. 2012. On Energy Efficiency In Collaborative Target Tracking In Wireless Sensor Network: A Review *Ieee Communication Surveys And Tutorials,* Pp, 1-13.

Fang, B. T. 1986. Trilateration And Extension To Global Positioning System Navigation. *Journal Of Guidance, Control, And Dynamics,* 9**,** 715-717.

Fang, J. & Li, H. 2009. *Ieee Transaction On Wireless Communications,* 8**,** 3822 - 3832

Fuemmeler, J. A., Atia, G. K. & Veeravalli, V. V. 2011. Sleep Control For Tracking In Sensor Networks. *Ieee Transaction On Signal Processing,* 59**,** 4354-4366.

Lin, J., Xiao, W., Lewis, F. & Xie, L. 2009. Energy-Efficient Distributed Adaptive Multisensor For Scheduling For Target Tracking In Wireless Sensor Networks. *Ieee Transaction On Instrumentation And Measurement,* 58**,** 1886 - 1896

Manolakis, D. E. 1996. Efficient Solution And Performance Analysis Of 3-D Position Estimation By Trilateration. *Ieee Transaction On Aerospace And Electronic Systems,* 32**,** 1239-1248.

Masazade, E., Niu, R. & Varshney, P. K. 2012. Dynamic Bit Allocation For Object Tracking In Wireless Sensor Networks. *Ieee Transaction On Signal Processing,* 60**,** 5048 - 5063.

Mukherjee, K., Gupta, S., Ray, A. & Wettergren, T. A. 2011. Statistical-Mechanics-Inspired Optimization Of Sensor Field Configuration For Detection Of Mobile Targets. *Ieee Transaction On Cybernetics,* 41**,** 783 - 791.

Onel, T., Ersoy, C. & Delic, H. 2009. Information Content-Based Sensor Selection And Transmission Power Adjustment For Collaborative Target Tracking. *Ieee Transaction On Mobile Computing,* 8.

Pattem, S., Poduri, S. & Krishnamachari, B. Energy-Quality Tradeoffs For Target Tracking In Wireless Sensor Networks. Ipsn'03 Proceedings Of The 2nd International Conference On Information Processing In Sensor Networks 2003 Palo Alto, Ca. 32-46.

Powers, J. W. 1966. Range Trilateration Error Analysis. *Ieee Transaction On Aerospace And Electronic Systems,* Aes-2**,** 572.

Thomas, F. & Ros, L. 2005. Revisiting Trilateration For Robot Localization. *Ieee Transaction On Robotics,* 21**,** 93-101.

Watfa, M. K. & Commuri, S. Optimal Sensor Placement For Border Perambulation. 2006 Ieee International Conference On Control Applications, 2006 Munich, Germany.

Yang, Z. & Liu, Y. 2008. Quality Of Trilateration: Confidence-Based Iterative Localization. *Ieee Transaction On Parallel And Distributed Systems,* 21**,** 631-640.

Zhao, F., Shin, J. & Reich, J. 2002. Information-Driven Dynamic Sensor Collaboration. *Ieee Signal Processing Magazine,* 19**,** 61-72.