An Energy-Efficient Lagrangean Relaxation-based Object Tracking Algorithm in Wireless Sensor Networks

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Abstract

The purpose of this paper is to study an energy-efficient object tracking in wireless sensor networks (WSNs). Such sensor network has to be designed to achieve energy-efficient object tracking for given arbitrary topology of sensor network. We particularly consider the frequency of two-way object movement of each pair of sensor nodes and link transmission cost. This problem is formulated as 0/1 integer-programming problem. A Lagrangean Relaxation-based (LR-based) heuristic algorithm is proposed for solving the optimization problem. The experimental results showed that the proposed algorithm gets a near optimization in the energy-efficient object tracking. Furthermore, the algorithm is very efficient and scalable in terms of the solution time.

Keywords: Wireless sensor networks, Object tracking, Lagrangean Relaxation

1. Introduction

The rapid growth in sensor technology and wireless communication has resulted in the development of wireless sensor networks (WSNs). WSNs have benefits of low cost and wireless communication capability. It consists of several sensors, sink nodes, and back-end system. These sensors work in coordination with collect physical information from the sensor field, and they can process and forward the information to the sink nodes. Finally, the back-ends can obtain global views according to the information provided by the sink nodes [3, 4].

Object tracking is the key application issue of WSNs which are widely deployed for military intrusion detection and wildlife animal monitoring. Object tracking wireless sensor networks have two critical operations [7-9]. One is monitoring. Sensor nodes are required to detect and track the movement states of mobile object. The other is reporting. The nodes sensing the object need to report their discoveries to the sink. These two operations are interleaved during the entire object tracking process. Our focus, in the prior studies [1, 2, 11], has been on developing strategies for reducing the energy consumption in reporting operations. For example, Fig. 2 illustrates a scenario of the event-driven reporting such as enemy intrusion detection and tracking in a battlefield. In [1], H.T. Kung, et al. propose a scalable message-pruning hierarchy tree called DAB for sensor tracking system. In [2, 11], Yu-Chee Tseng, et al. propose two message-pruning tree structures called DAT and Z-DAT for object tracking.

This study is an extension of the work in [1, 2, 11]. The previous studies are expanded to the energy-efficient object tracking in wireless sensor networks. We focus on the problem of constructing an energy-efficient wireless sensor networks for object tracking services using the object tracking tree. Therefore, we motivate to propose a heuristic strategy to cope with the problem with a given sensor network arbitrary topology, and we particularly consider link transmission cost and two-way object moving frequency of in-sensor field and incoming-outgoing sensor field. The total communication cost can be computed and minimized by object tracking tree during planning stage.

The calculating communication cost is different from that of prior studies [1, 2, 11]. First, we consider the frequency of two-way object movement of each pair of sensor nodes because the round-trip traffic cost of each pair of sensor nodes is different. Second, we consider the link transmission cost since each link transmission cost is also different. Fig. 1 illustrates an example of calculating communication cost. The weight of each solid link represents link transmission cost between a pair of adjacent communication nodes or between a pair of sensor node and communication node, and the weight of each dash link represents the object moving frequency between a pair of adjacent sensors. For example, communication cost is 40 (10*4) when object moves from sensor *x* to sensor *y*, and communication cost is 64 ((6+2)*8) when object moves from sensor *y* to sensor *x*.

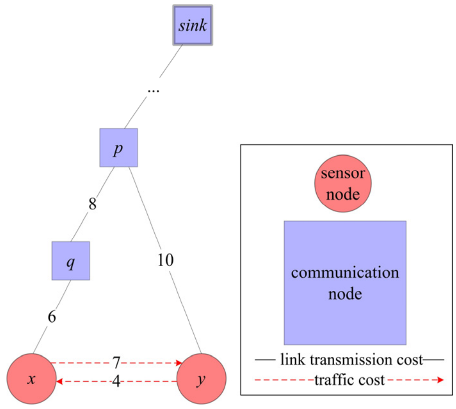

Fig. 1. Example of calculating communication cost.

In this paper, we formulate the problem as a 0/1 integer programming problem where the objective function is to minimize the total communication cost subject to routing, tree, and variable-transformation constraints. Because an object tracking tree in a weighted graph spans a given sensor nodes, and the tree is used to minimize total communication cost. Therefore, constructing the object tracking tree is NP-complete problem [10]. We use the Lagrangean Relaxation-based (LR-based) heuristic algorithm to solve the sub-problem and obtain a primal feasible solution.

The problem is formulated as a linear optimization-based problem with three different decision variables: paths, tree links, and tracking links. Paths are the original destination pairs between sensor nodes and *sink* node. Tree links are the links of object tracking tree. Tracking links are the links when object moves from sensor *x* to sensor *y*, and then sensor *y* delivers tracking information upward to the first common ancestor via the tree links [1]. For example, tracking links are the links between communication node *p* and sensor node *y* in Fig. 1. To fulfill the timing and the quality requirement of the optimal decisions, the Lagrangean Relaxation method, which has been successfully adopted to solve many famous NP-complete problems [5, 6], is used. In the further computational experiments, the proposed object tracking algorithm is expected to be efficient and effective in dealing with the complicated optimization problem.

From papers review, this study differs from the prior works in two points [1, 2, 11]. First, we consider the frequency of two-way object movement of each pair of sensor nodes and link transmission cost. Second, we present a LR mathematical model to describe the optimization problem and propose LR-based heuristic algorithm to solve the problem.

The rest of this paper is organized as follows. The problem and mathematic model are described in sections 2 and 3, respectively. Additionally, the solution approach is presented in section 4. Furthermore, the computational results are discussed in section 5. Finally, conclusion is presented in section 6.

2. Problem Description

Our approach uses hierarchical object tracking tree to record information about presence of the object and to keep this information up to date. Sensor nodes are required to detect and track the movement states of mobile object. The information about presence of the detected object is stored at communication nodes and each communication node particularly stores the set of object that was detected jointly by its descendants. This set is called the detected set. For example, the detected set of a sensor at a leaf node consists of just the objects within the sensor's detection range while the sink node's detected set contains all objects presented in the sensor field [1]. For example, Fig. 2 illustrates a scenario of object tracking. Sensor *u* will detect the object and deliver the object's location information to *sink* node when object enters the sensor filed, and sensor *v* will only forward the new location information to communication node *c* when object moves from sensor *u* to sensor *v*. Finally, sensor *z* will forward the leaving information to *sink* node when object leaves sensor field from sensor *z*.

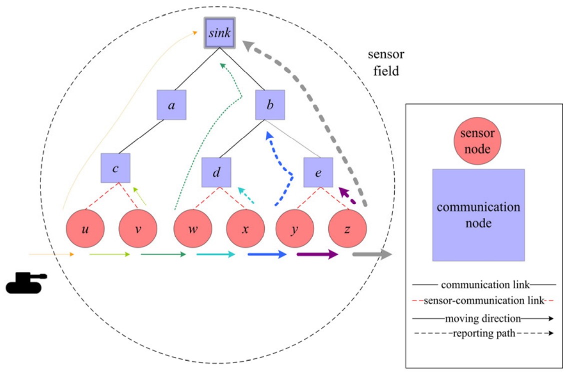

Fig. 2. Example of object tracking.

The energy-efficient object tracking in WSNs problem is modeled as a graph, $G(V,L)$, where V are sensor nodes and communication nodes (including *sink* node) distributed in a two-dimensional plane and link L (e.g., (i, j) indicates that node j is covered by i's radio).

For example, the sensor sub-graph in Fig. 3 illustrates a 2D sensor field with each edge connecting a pair of adjacent sensors. Each link weight is object moving frequency of each pair of sensor nodes.

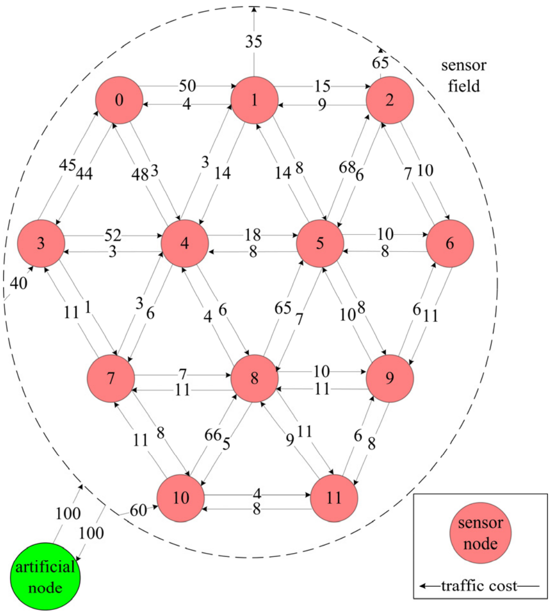

Fig. 3. Example of 2D sensor sub-graph.

Fig. 4 illustrates a 2D sensor field's tracking sub-graph with each edge connecting a pair of adjacent communication nodes or sensor-communication nodes. Each link weight represents link transmission cost.

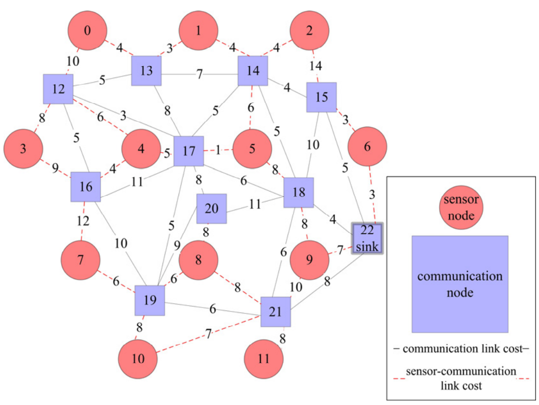

Fig. 4. Example of 2D tracking sub-graph.

In this paper, we consider a given sensor network arbitrary topology, two-way object moving frequency of in-sensor field and incoming-outgoing sensor field, and link transmission cost. The sensor field consists of sensor nodes and communication nodes. We deploy hierarchical network topology architecture. All sensor nodes send data to upper layer communication nodes. Eventually, the sensing information is sent to *sink* node.

A good tracking method is characterized by a low total communication cost [1]. Given a sensor graph, we can compute the total communication cost.

We define the total communication cost for graph G as the sum of counting the number of events transmitted in G:

Total Communication Cost (G) =

$$\sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} t^{xy}_{(i,j)} r_{xy} a_{(i,j)} + \sum_{s\in S}\sum_{(i,j)\in L} z^{s}_{(i,j)}(r_{os}+r_{so})a_{(i,j)}$$

Where S is the set of all sensor nodes and L is the set of all links. The decision variable $t^{xy}_{(i,j)}=1$ if $z^{x}_{(i,j)}=0 \cap z^{y}_{(i,j)}=1$ (reporting object's location uses the link (i, j) when object moves from sensor x to sensor y) and 0 otherwise. The decision variable $z^{s}_{(i,j)}=1$ if the sensor node s uses the link (i, j) to reach the *sink* node and 0 otherwise. $a_{(i,j)}$ is the transmission cost associated with link (i, j). r_{xy} is the frequency of object movement from x to y, r_{os} is traffic frequency while entering sensor field, and r_{so} is traffic frequency when leaving sensor field.

3. Problem Formulation

The notations used to model the problem are listed as follows.

Table 1
Notations for the given parameters

Given Parameters	
Notation	Description
S	The set of all sensor nodes.
C	The set of all communication nodes, including *sink* node.
R	The set of the frequency of object movement from x to y, $\forall x, y \in S \cup \{o\}$, $x \neq y$.
L	The set of all links, $(i, j) \in L$, $i \neq j$.
A	The set of transmission cost $a_{(i,j)}$ associated with link (i, j).
P_s	The set of all candidate paths p between any pair (s, *sink*), $\forall s \in S$.
o	Artificial node outside the sensor field.

Table 2
Notation for the indicate parameter

Indicate Parameter	
Notation	Description
$\delta_{p(i,j)}$	The indicator function which is 1 if link (i, j) is on path p and 0 otherwise.

Table 3
Notations for the decision variables

Decision Variables	
Notation	Description
x_p	1 if the sensor node s uses the path p to reach the *sink* node and 0 otherwise, $\forall s \in S$, $p \in P_s$.
z^s	1 if the sensor node s uses the link (i, j) to reach the *sink* node and 0 otherwise.
$t^{xy}_{(i,j)}$	1 if $z^x_{(i,j)} = 0 \cap z^y_{(i,j)} = 1$ (reporting object's location uses the link *(i, j)* when object moves from sensor x to sensor y) and 0 otherwise, $x \neq y$.

Problem (IP):

Objective function:

$$Z_{IP} = \min \sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} t^{xy}_{(i,j)} r_{xy} a_{(i,j)} + \sum_{s\in S}\sum_{(i,j)\in L} z^{s}_{(i,j)} (r_{os} + r_{so}) a_{(i,j)} \qquad \text{(IP)}$$

subject to:

$$\sum_{p\in P_s} x_p = 1 \qquad \forall s \in S \qquad (1)$$

$$\sum_{j\in C} z^s_{(i,j)} = 1 \qquad \forall s \in S,\ i \in S \cup C - \{sink\} \qquad (2)$$

$$\sum_{p\in P_s} x_p \delta_{p(i,j)} \le z^s_{(i,j)} \qquad \forall s \in S,\ (i,j) \in L \qquad (3)$$

$$2t^{xy}_{(i,j)} \le z^y_{(i,j)} - z^x_{(i,j)} + 1 \qquad \forall x, y \in S, (i,j) \in L \qquad (4)$$

$$z^y_{(i,j)} - z^x_{(i,j)} + 1 \le t^{xy}_{(i,j)} + 1 \qquad \forall x, y \in S, (i,j) \in L \qquad (5)$$

$$\sum_{(i,j)\in L} t^{xy}_{(i,j)} \ge 1 \qquad \forall x, y \in S \qquad (6)$$

$$x_p = 0 \text{ or } 1 \qquad \forall s \in S,\ p \in P_s \qquad (7)$$

$$z^s_{(i,j)} = 0 \text{ or } 1 \qquad \forall s \in S,\ (i,j) \in L \qquad (8)$$

$$t^{xy}_{(i,j)} = 0 \text{ or } 1 \qquad \forall x, y \in S, (i,j) \in L. \qquad (9)$$

The objective function (IP) of this problem is to minimize the total communication cost subject to:

Constraint (1): Routing constraint which uses one path from sensor node s to *sink* node only.

Constraint (2): Tree constraint of avoiding cycle. Any node's outgoing link to communication node is equal to 1 on the object tracking tree.

Constraint (3): Routing constraint. Once the path, x_p, is selected and the link (i, j) is on the path, the decision variable, $z^s_{(i,j)}$, must be enforced to equal 1.

Constraint (4-5): There are variable-transformation constraints. If $z^x_{(i,j)} = 0 \cap z^y_{(i,j)} = 1$, reporting object's location will use the link (i, j) when object moves from sensor x to sensor y,

$t^{xy}_{(i,j)}$ must be enforced to equal 1 and 0 otherwise.

Constraint (6): For all $\sum_{(i,j)\in L} t^{xy}_{(i,j)}$ must be greater than or equal to 1. This is redundant constraint.

Constraint (7-9): Decision variables x_p, $z^s_{(i,j)}$, and $t^{xy}_{(i,j)}$ equal 0 or 1.

4. Solution Approach

4.1 Lagrangean Relaxation

Using the Lagrangean Relaxation method, successfully adopted to solve many famous NP-complete problems [5, 6], we can transform the primal problem (IP) into the following Lagrangean Relaxation problem (LR) where constraints (3), (4), and (5) are relaxed. For a vector of non-negative Lagrangean multipliers, a Lagrangean Relaxation problem of (IP) is given by:

Problem (LR):

Objective function:

$$\begin{aligned}
& Z_{LR}(u^1_{s(i,j)}, u^2_{xy(i,j)}, u^3_{xy(i,j)}) \\
&= \min\{\sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} t^{xy}_{(i,j)} r_{xy} a_{(i,j)} \\
&+\sum_{s\in S}\sum_{(i,j)\in L} z^s_{(i,j)}(r_{os}+r_{so})a_{(i,j)} \\
&+\sum_{s\in S}\sum_{(i,j)\in L}\sum_{p\in P_s} u^1_{s(i,j)} x_p \delta_{p(i,j)} \\
&-\sum_{s\in S}\sum_{(i,j)\in L} u^1_{s(i,j)} z^s_{(i,j)} \\
&+\sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} u^2_{xy(i,j)} 2t^{xy}_{(i,j)} \\
&-\sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} u^2_{xy(i,j)}(z^y_{(i,j)} - z^x_{(i,j)} + 1) \\
&+\sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} u^3_{xy(i,j)}(z^y_{(i,j)} - z^x_{(i,j)} + 1) \\
&-\sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} u^3_{xy(i,j)}(t^{xy}_{(i,j)} + 1)\}
\end{aligned} \qquad \text{(LR)}$$

subject to: (1), (2), (6), (7), (8), and (9).

Where $u^1_{s(i,j)}$, $u^2_{xy(i,j)}$, and $u^3_{xy(i,j)}$ are Lagrangean multipliers and $u^1_{s(i,j)}$, $u^2_{xy(i,j)}$, and $u^3_{xy(i,j)} \geq 0$. To solve (LR), we can decompose (LR) into the following four independent and easily solvable optimization sub-problems.

$$Z_{LR} = Z_{sub1} + Z_{sub2} + Z_{sub3} + Z_{sub4}$$

Sub-problem 1: (related to decision variable $t^{xy}_{(i,j)}$)

Objective function:

$$\begin{aligned}
& Z_{sub1}(u^2_{xy(i,j)}, u^3_{xy(i,j)}) \\
&= \min\sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} t^{xy}_{(i,j)}(r_{xy}a_{(i,j)} + 2u^2_{xy(i,j)} - u^3_{xy(i,j)})
\end{aligned} \qquad \text{(sub1)}$$

subject to: (6) and (9)

Sub-problem 2: (related to decision variable x_{p_s})

Objective function:

$$Z_{sub2}(u^1_{s(i,j)}) = \min\sum_{s\in S}\sum_{(i,j)\in L}(u^1_{s(i,j)}\sum_{p\in P} x_p \delta_{p(i,j)}) \qquad \text{(sub2)}$$

subject to: (1) and (7).

Sub-problem 3: (related to decision variable $z^s_{(i,j)}$)

Objective function:

$$\begin{aligned}
& Z_{sub3}(u^1_{s(i,j)}, u^2_{xy(i,j)}, u^3_{xy(i,j)}) \\
&= \min\sum_{s\in S}\sum_{(i,j)\in L}[(r_{os}+r_{so})a_{(i,j)} - u^1_{s(i,j)} \\
&+\sum_{x\in S}(u^3_{xs(i,j)} - u^2_{xs(i,j)}) \\
&-\sum_{y\in S}(u^3_{sy(i,j)} - u^2_{sy(i,j)})]z^s_{(i,j)}
\end{aligned} \qquad \text{(sub3)}$$

subject to: (2) and (8).

Sub-problem 4: (Constant Part)

Objective function:

$$Z_{sub4}(u^2_{xy(i,j)}) = -\sum_{x\in S}\sum_{y\in S}\sum_{(i,j)\in L} u^2_{xy(i,j)} \qquad \text{(sub4)}$$

According to the weak Lagrangean duality theorem [5, 6], $Z_D(u^1_{s(i,j)}, u^2_{xy(i,j)}, u^3_{xy(i,j)})$ is a lower bound (LB) on Z_{IP} when $u^1_{s(i,j)}$, $u^2_{xy(i,j)}$, and $u^3_{xy(i,j)} \geq 0$.

The following dual problem (D) is then constructed to calculate the tightest lower bound.

Dual Problem (D):

Objective function:

$$Z_D = \max Z_D(u^1_{s(i,j)}, u^2_{xy(i,j)}, u^3_{xy(i,j)}) \qquad \text{(D)}$$

subject to:

$$u^1_{s(i,j)},\ u^2_{xy(i,j)},\ \text{and}\ u^3_{xy(i,j)} \geq 0 \qquad (10)$$

There are several methods for solving the dual-mode problem (D). One of the most popular is the subgradient method.

4.2 Getting Primal Feasible Solutions

After optimally solving the Lagrangean dual problem, we get a set of decision variables and develop LR-based heuristic algorithm to tune these decision variables. A set of feasible solutions of the primal problem (IP) then can be obtained. The primal feasible solution is an upper bound (*UB*) of the problem (IP), and the Lagrangean dual problem solution guarantees the lower bound (*LB*) of the problem (IP). Iteratively, by solving getting primal feasible solution and Lagrangean dual problem, we get *UB* and *LB*, respectively. The duality gap between *UB* and *LB*, computed by $|(UB - LB)/LB| * 100\%$, illustrates the optimality of problem solution. The smaller duality gap computed, the better the optimality.

A LR-based primal heuristic algorithm is listed in Fig. 5 and object tracking tree algorithm is listed in Fig. 6.

Algorithm Primal_Heuristic

Step 1 Using the shortest path tree algorithm (SPT) to find the initial primal value.

Step 2 We adjust arc weight $c_{s(i,j)} = \sum_{s \in S} u^1_{s(i,j)}$ for each $(i,j) \in L$ and then run the Dijkstra algorithm to get the solution set of $\{x_p\}$.

Step 3 Once $\{x_p\}$ is determined, $t^{xy}_{(i,j)}$ and $z^s_{(i,j)}$ are also determined.

Step 4 We can have an object tracking tree now, and then iteratively execute the **Step 2~3** with LR multipliers that can be updated from dual mode problem.

Fig. 5. The LR-based primal heuristic algorithm.

Algorithm Object_Tracking_Tree
begin
  Initialize the Lagrangean multiplier vector (u^1, u^2, u^3) to be zero vectors;
  UB:=total communication cost of shortest path tree; LB:=very small number;
  improve_counter:=0;
  step_size_coefficient:=2;
  for *iteration*:=1 **to** *Max_Iteration_Number* **do**
  begin
    run sub-problem(SUB1);
    run sub-problem(SUB2);
    run sub-problem(SUB3);
    run sub-problem(SUB4);
    calculate Z_D;
  if Z_D>LB
    then LB:=Z_D and improve_counter:=0;
    else improve_counter:= improve_counter+1;
  if improve_counter:= improve_Threshold
    then improve_counter:=0; $\lambda := \lambda / 2$;
    run Primal_Heuristic Algorithm;
  if ub<UB
    then UB:=ub; /* ub the the newly computed upper bound */
    run update-step-size;
  run update-Lagrangean-multiplier;
  end;
end;

Fig. 6. The object tracking tree algorithm.

5. COMPUTATIONAL EXPERIMENTS

To evaluate the performance of the proposed algorithm, we conduct an experiment. The performance is assessed in terms of total communication cost.

5.1 Scenario

The proposed algorithm is coded in C under a Microsoft Visual C++ 6.0 development environment. All the experiments are performed on a Core 2 Duo 2.2G Hz PC running Microsoft Windows Vista. The algorithm is tested on a 2D sensor field. We distribute sensor nodes and communication nodes in sensor field, as shown in Figs. 3 and 4.

5.2 Experimental Results

In order to evaluate our proposed heuristic algorithm, we compare this one with other heuristic algorithm, such as shortest path tree (SPT) algorithm. With the exception of this SPT algorithm, the proposed heuristic algorithm can be also compared with dual mode problem value (Low Bound, *LB*).

Fig. 7 shows an example of LR-based object tracking tree for in-sensor field and incoming-outgoing sensor field object tracking. Fig. 8 shows an example of LR-based object tracking tree for in-sensor field object tracking, with no object moving frequency for incoming-outgoing sensor field.

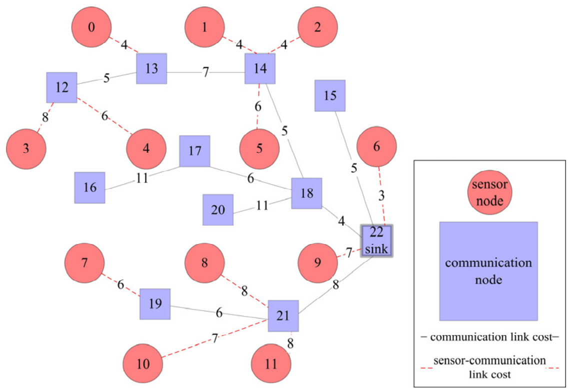

Fig. 7. Example of LR-based object tracking tree for in-sensor field and incoming-outgoing sensor field object tracking.

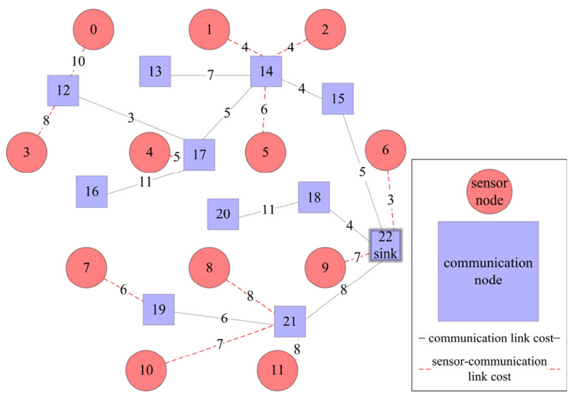

Fig. 8. Example of LR-based object tracking tree for in-sensor field object tracking.

Figs. 9 and 10 show two examples of the trend line for getting the primal problem solution values (*UB*) and dual mode problem values (*LB*). The *UB* curves tend to decrease to get the minimum feasible solution. In contrast, the *LB* curves tend to increase and converge rapidly to reach the optimal solution. The LR-based method ensures the optimization results between *UB* and *LB* so that we can keep the duality gaps as small as possible in order to improve our solution quality and achieve near optimization. In these examples the duality gaps between *UB* and *LB* are 0% for in-sensor field and incoming-outgoing sensor field object tracking and 1.2% for in-sensor field object tracking.

This study shows the best finding for the minimum total communication cost by the proposed algorithm. Eventually, the total communication costs of SPT algorithm are 10559 and 5019, the total communication costs of LR-based algorithm (*UB*) are 9955 and 4568, and the dual mode problem values (*LB*) are 9955 and 4513.

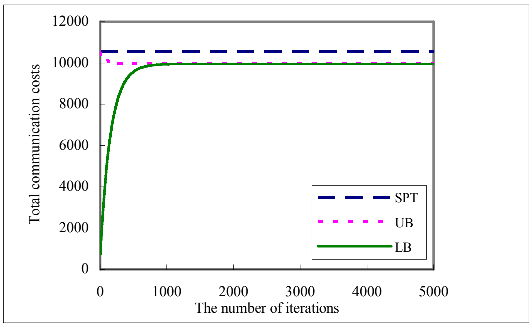

Fig. 9. The execution results of LR-based algorithm for in-sensor field and incoming-outgoing sensor field object tracking.

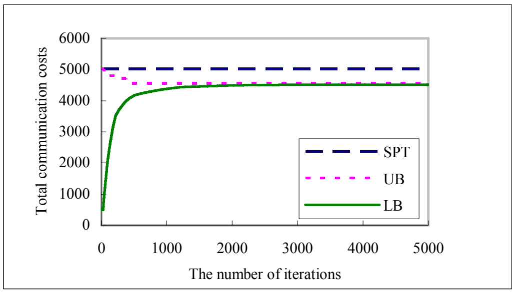

Fig. 10. The execution results of LR-based algorithm for in-sensor field object tracking.

Table 4 shows that the time complexity of our LR-based solution is dominated by Lagrangean dual problem. The Lagrangean dual problem is to solve the above four sub-problems with the maximum number of iteration *I*.

Table 4
The time complexity of LR-based object tracking tree algorithm

LR-based Solution Approach	
Sub-problem	Time Complexity
Sub-problem (SUB1)	$O(\|S\|^2\|L\|)$
Sub-problem (SUB2)	$O(\|S\|\|L\|)$
Sub-problem (SUB3)	$O(\|S\|^2\|L\|)$
Sub-problem (SUB4)	$O(\|S\|^2\|L\|)$
Lagrangean dual problem	$O(I\|S\|^2\|L\|)^*$

*Where parameter *I* means the maximum number of iterations

6. Conclusions

This study proposes an object tracking algorithm in wireless sensor networks. To our best knowledge, the proposed algorithm is truly novel and it has not been yet discussed in previous researches. This study first formulates the problem as a 0/1 integer programming problem, and then proposes a Lagrangean Relaxation-based heuristic algorithm to solve the optimization problem.

The experimental results show that the algorithm is not only better than the other heuristic algorithm, such as SPT, but the duality gap is also small. In other word, the proposed heuristic algorithm can improve about 6% and 9.9% respectively in energy consumption when compared with SPT and achieve the near optimal solution since the duality gaps are only

0% and 1.2%. Therefore, the results show that the proposed LR-based algorithm can achieve energy-efficient object tracking. Furthermore, the algorithm is very efficient and scalable in terms of the solution time.

We are planning to further investigate response time model based on object tracking application requirements and heuristic algorithms in the near future. In addition, we are looking into the tradeoff of total communication cost with various system issues, such as response time, report frequency, number of sinks, etc.

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