Wireless Sensor Network, **2011, 3, 295-299**
doi:10.4236/wsn.2011.38030 Published Online August 2011 (http://www.SciRP.org/journal/wsn)

Sensor Scheduling Algorithm Target Tracking-Oriented

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Received June 17, 2011; *revised July* 21, 2011; *accepted July* 31, 2011

Abstract

Target tracking is a challenging problem for wireless sensor networks because sensor nodes carry limited power recourses. Thus, scheduling of sensor nodes must focus on power conservation. It is possible to extend the lifetime of a network by dynamic clustering and duty cycling. Sensor Scheduling Algorithm Target Tracking-oriented is proposed in this paper. When the target occurs in the sensing filed, cluster and duty cycling algorithm is executed to schedule sensor node to perform tracking task. With the target moving, only one cluster is active, the others are in sleep state, which is efficient for conserving sensor nodes' limited power. Using dynamic cluster and duty cycling technology can allocate efficiently sensor nodes' limited energy and perform tasks coordinately.

Keywords: Wireless Sensor Network, Sensor Scheduling, Target Tracking, Collaborative Signal Processing, Dynamic Clustering

1. Introduction

Wireless sensors network is becoming an important topic of research with development of digital circuitry, wireless communications and Micro Electro Mechanical Systems, which is composed of many tiny sensor nodes built in one or more sensors, computation and communication unit, and a power supply. Sensor nodes may be deployed to perform measurements in environments including instrumentation of rotating machinery and so on or monitoring the movements of small animal [1].

Wireless sensor network is a power-limited and multiuser distributed system, so it is necessary to make sensor nodes operate collaboratively. CSP (collaborative signal processing) is a new research field in wireless sensor networks aiming at developing new algorithms for processing massive information sensed by sensor nodes. It is critical for wireless sensor network using CSP to dynamically allocate resources among sensor nodes [2].

A typical application in wireless sensor networks is target tracking, such as security surveillance and wildlife habitat monitoring. Target tracking contains a lot of collaboration between individual sensors to perform complex signal processing algorithms such as Kalman filtering, Bayesian data fusion and other optimal algorithm. Thus, energy management is a key task during target moving, which affects energy consumption and network lifetime. Cooperative strategies for target tracking are based on the following idea: with target moving, a set of nodes are selected to perform task, and the other nodes can be turned off for saving energy. The node selection is based on special algorithm considering nodes' residual energy, distance form target and so on. Thus, considerable energy can be potentially conserved [3,4].

Xu Y *et al*. proposed a geographical adaptive fidelity (GAF) algorithm that keeps energy by identifying nodes equivalent from a routing perspective. GAF can keep a constant level of fidelity by turning off unnecessary nodes. Simulation shows that network lifetime increases proportionally to node density. GAF can be used for extending network lifetime by exploiting redundancy in order to keep energy [5].

Jianyong Lin *et al.* presented an adaptive multisensor scheduling scheme for target tracking in Wireless Sensor Network, which is divided into three steps. First, the sampling interval is set by a predetermined tracking accuracy value. Then, some sensors are chosen to form a cluster for performing task. Last, the cluster head is determined based on the predicted energy consumption. A Monte Carlo method is employed to predict approximately the target state. The proposed scheme can not only reduce the energy consumption and improves the tracking reliability, but also resist the uncertainty of the process noise form simulation results [6].

In this paper, we propose sensor scheduling algorithm target tracking-oriented. Deployment of sensor nodes adopts honeycomb structure to increase one-hop coverage area. When the target occurs in the sensing filed, cluster and duty cycling algorithm is executed to schedule sensor node to perform tracking task. The Kalman filter is employed to estimate next possible location of target. With the target moving, only one cluster is active, the other are in sleep state, which is efficient for conserving sensor nodes' limited power. Using dynamic cluster and duty cycling technology can make good use of each sensor nodes' limited energy and perform tasks coordinately.

2. Prolonging the Lifetime of Sensor Network

2.1. Energy Consumption of Sensor Nodes

A sensor node consists of a sensing unit, a processing unit, a transceiver unit and a power unit as shown in **Figure 1**, which a limited energy (< 0.5 Ah, 1.2 V). Moreover, sometimes it may be impossible to replace power resources. So, sensor node lifetime is mainly decided by battery lifetime. Power conservation and power management of sensor nodes is a key problem for wireless sensor network.

Energy consumption of node subsystems is shown in **Figure 2** [7]. There are four possible states for sensor node's radio to select: transmit, receive, idle, or sleep. It is obtained that the: Energy Consumption of Sensor Node's radio component is:

$$E_{TX} \approx E_{RX} \approx E_{IDLE} >> E_{SL}$$

Thus, it is judicious to completely shut down the radio when it is not transmitting or receiving data in order to keep power.

2.2. Clustering of Sensor Nodes

Sensor nodes in WSN can be divided into some groups called clusters to realize data gather with efficient network organization, in which has a cluster head (CH) and a number of member nodes. Clustering produces a two-layer hierarchy in WSN. Cluster heads (CHs) belong to the higher layer while member nodes the lower layer. The members of a cluster can communicate with their CH directly. A CH can forward the fused data to the central base station through other CHs.

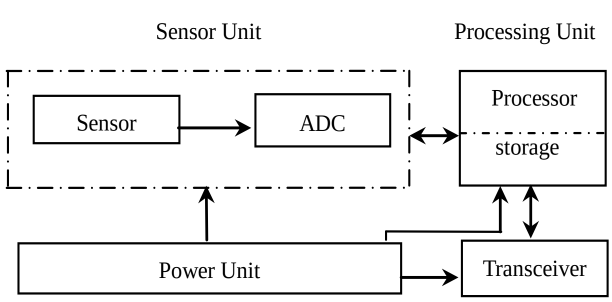

Figure 1. The components of a sensor node.

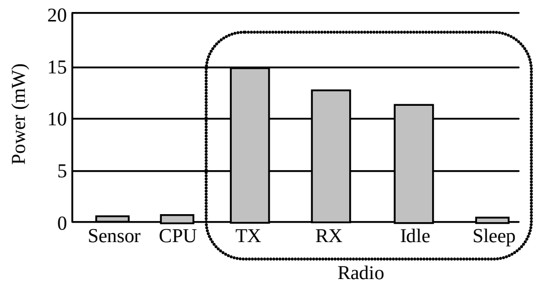

Figure 2. Energy consumption of sensor nodes.

The member nodes send their data to the respective CHs. Then the CHs fuse the data and transmitted them to the base station through other CHs. CHs may lose more energy because of transmitting data over longer distances.

2.3. Duty Cycling

Duty cycling is very important in wireless sensor for conserving energy, which makes the radio transceiver be in the sleep mode while communication is not required. Thus, sensor nodes change between active and sleep state based on network activity, which is known as duty cycling. Duty is cycling defined as time slots that nodes are active during their lifetime. For target tracking, since sensor nodes perform a task cooperatively, it is necessary to coordinate their sleep/wakeup times. A sleep/wakeup scheduling algorithm is employed to decide state transformation (active to sleep and vice versa) of sensor nodes.

3. Deployment of Sensor Nodes

Different shapes to forming node into clusters have been proposed for deploying nodes, such as circle, quadrilateral, and hexagon. The honeycomb is often used because it corresponds to the shape of the radio transmission range, which may result in overlapping between clusters or uncovered areas. The hexagon is an ideal shape for clustering a large area into adjacent, no overlapping areas, which can be proved as follows.

Quadrilateral structure for parting sensing region is shown in **Figure 3**, in which nodes are divided into small cluster. The clusters are defined as that two neighboring clusters A and B, where all nodes in A can communicate with all nodes in B and vice versa.

Note that transmitting range is R, so the distance between two possible farthest nodes in any two neighboring clusters, for example node 1 in cluster A and node 2 in cluster B (**Figure 3**), must not be larger than R. Based on marked value in **Figure 3**, functions can be expressed as follow:

$$a^2 + (2a)^2 \le R^2 \quad (1)$$

$$2a^2 = r^2 \quad (2)$$

$$a \le R/\sqrt{5} \quad (3)$$

Honeycomb structure for parting sensing region is shown in **Figure 4**; functions can be expressed based on marked value in **Figure 4**.

$$b^2 + (2\sqrt{3}b)^2 \le R^2 \quad (4)$$

$$b \le R/\sqrt{13} \quad (5)$$

Thus, area of quadrilateral and each honeycomb can be expressed by:

$$S_q = a^2 = R^2/5 = 0.2R^2 \quad (6)$$

$$S_h = 3\sin 60° b^2 = \frac{3\sqrt{3}}{26} R^2 \approx 0.2R^2 \quad (7)$$

Note that the one-hop coverage area of quadrilateral structure is $S_{qc} = 5S_q = R^2$ and the one-hop coverage area of honeycomb structure forwarding is $S_{hc} = 7\,S_h \approx 1.4\,R^2$, so the one-hop coverage area of honeycomb structure is about 40% larger than that of quadrilateral structure.

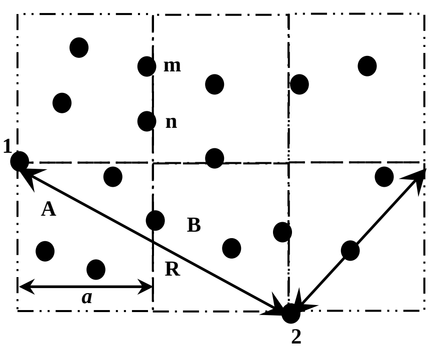

Figure 3. Quadrilateral structure.

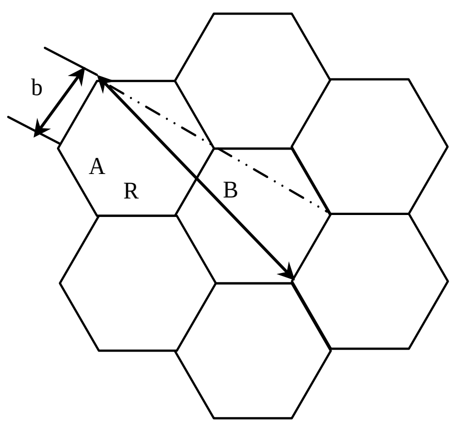

Figure 4. Honeycomb structure.

4. Sensor Scheduling During Target Moving

4.1. Dynamic Clustering

Dynamic cluster architectures means that clusters will be formed with certain events of interest coming, such as target appear. If a sensor node with sufficient energy and computational power detects signals of interest, it would be selected as a CH (cluster head). Sensors near to the active CH are invited to join the cluster and send their information to the CH.

At any time instant only one cluster is active with target moving, in which sensors nodes are in the active state and all other sensors are shut down (**Figure 5**) Sensor scheduling mechanism properly adapt to a scalable and dynamic network topology. The network activity can be set in time slots. Then, active sensor nodes are selected at the beginning of time slot corresponding to trajectory of target. Active node selection is chosen according to the connectivity, power efficiency and so on.

Sensor scheduling problem is employed to select sensors to form cluster dynamically in order to optimize the tracking performance of the targets. The sensor nodes being activated at time t_i must be chosen at or before time $t_i - T_K$, where T_K is the time needed to select and activate a sensor cluster.

4.2. Maximum Entropy Clustering

The objective of a clustering algorithm is the assignment of a set of M feature vectors $x_i \in X$ into k clusters, which are represented by the prototypes $c_j \in$ C. The certainty of the assignment of the feature vectors $x_i \in X$ into various clusters is measured by the membership functions u_{ij} [0, 1], $j = 1, 2, k$, ($\sum_{ij}^{i} u_{ij} = 1$).

For a given set of membership functions, the distortion between the feature vectors $x_i \in X$ and the prototypes $c_j \in C$ is measured by[13-15].

$$D(u_{ij} \in U, c_i \in C) = \frac{1}{M} \sum_{i=1}^{M} \sum_{j=1}^{k} u_{ij} d(x_i, c_j) \quad (8)$$

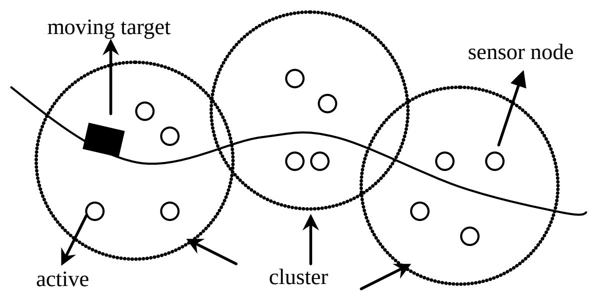

Figure 5. Dynamic cluster with target moving.

where d (x_i, c_j) is a metric of the distance between the feature vector $x_i \in X$ and the prototype $c_j \in C$,

$$d\left(x_i - c_i\right) = \left\|x_i - c_i\right\|^2 \quad (9)$$

In the maximum uncertainty or minimum selectivity phase, the clustering process is based on the minimization of the negative entropy, given by

$$E*\left(u_{ij} \in U\right) = \sum_{i=1}^{M} \sum_{j=1}^{k} u_{ij} \log u_{ij} \quad (10)$$

Assume that the sensor network including k numbers of sensor nodes can be divided into M numbers of clusters, and the matrix of cluster head is $\mathrm{H} = \left\{\mathrm{H}_1, \mathrm{H}_2, \cdots, \mathrm{H}_z\right\}$ and u_{ij} is the degree of membership of node x_i in cluster j.

$$I\left(u, H\right) = \sum_{i=1}^{M} \sum_{j=1}^{k} u_{ij} d_{ij}^2 + \frac{1}{\lambda} \sum_{i=1}^{M} \sum_{j=1}^{k} u_{ij} \log u_{ij} \quad (11)$$

$$u_{ij}^{(l+1)} = e^{-\lambda d_{ij}} \Big/ \sum_{k=1}^{c} e^{-\lambda d_{ij}} \quad (12)$$

$$H_i^{(l+1)} = \sum_{j=1}^{k} u_{ij}^{(l+1)} x_j \Big/ \sum_{j=1}^{k} u_{ij}^{(l+1)} \quad (13)$$

The Clustering process is described as follows:

1) Initialization of cluster head is assumed as

$$H^{(0)} = \left\{H_1^{(0)}, H_2^{(0)}, \cdots, H_c^{(0)}\right\}$$

2) Defining convergence threshold ε

3) Updating u_{ij} and cluster head with expressions (12) and (13) until

$$\max\left(\left\|H_i^{(l+1)} - H_i^{(l)}\right\|\right) < \varepsilon$$

4.3. Predication of Trajectory

During the target tracking, when to wakeup sensor nodes to form cluster for performing tracking task is mainly based on the location of target in next time slot. Thus, it is necessary to estimate precisely the trajectory of targets. In this paper, we use Kalman filter to predict the trajectories of target. The Kalman filter is a set of mathematical equations that is efficient to estimate the state of a process, because it supports estimations of past, present, and even future states.

The Kalman filter estimates a process using feedback control, so the equations for the Kalman filter include time update equations and measurement update equations. The time update equations represent projecting forward the current state and error covariance estimates to achieve the a priori estimates for the next time step [16].

The state vectors of all targets at time t_k is expressed by $x_k = \left[x_k^1, x_k^2, \cdots, x_k^n\right]$, where x_k^i is the state vector of target i and n represents the number of targets. The state equation of the n targets is set by

$$X_k = A \cdot X_{k-1} + W_{k-1} \quad (14)$$

with a measurement that is

$$Z_k = H_k + V_k \quad (15)$$

The random variables W_k and V_k represent the process and measurement noise (respectively).They are assumed to be independent (of each other), white, and with normal probability distributions

Where A is a linear function, and W_k is independent white noise. Five basic equations of Kalman filter (time update equations, measurement update equations) is given by [16]

$$X\left(k\middle|k-1\right) = A \cdot X\left(k-1\middle|k-1\right) + W\left(k\right) \quad (16)$$

$$P\left(k\middle|k-1\right) = A \cdot P\middle|k-1) = A \cdot P\left(k-1\middle|k-1\right)A^T + Q \quad (17)$$

$$X\left(k\middle|k\right) = X\left(k\middle|k-1\right) + K_g\left(k\right)\left(Z\left(k\right) - H \cdot X\left(k\middle|k-1\right)\right) \quad (18)$$

$$K_g = P\left(k\middle|k-1\right) \cdot H' \Big/ \left(H \cdot P\left(k\middle|k-1\right)H^T + R\right) \quad (19)$$

$$P\left(k\middle|k\right) = \left(I - K_g\left(k\right) \cdot H\right) P\left(k\middle|k-1\right) \quad (20)$$

The process is repeated with the previous a posteriori estimates used to predict the new a priori estimates with each time and measurement update.

4.4. Sensor Scheduling

When a target appears in the sensor network, it can be sensed when sensor nodes' detected signal strength beyond a predefined value. Then, sensor nodes are selected to form a cluster dynamically. There are a cluster head and several member nodes in each cluster. The sensor information is passed on to cluster heads where, in turn, transmit information to the base station.

With the target moving, different sensor nodes are chosen to form another cluster and the nodes in this cluster are awakened while make other sensor nodes be in sleep mode based on the prediction of trajectory of target and node' energy and location. Thus, it is possible to save energy during tracking with duty cycling and cluster technology.

5. Conclusions

In this paper, we propose sensor scheduling algorithm target tracking-oriented. We try to solve the problem how to scheduling sensor nodes to extend network lifetime during target tracking. We utilize dynamic cluster and duty cycling technology in order to shedule sensors that perform tasks be in the active state and all other sensors are in the sleep state. In later research, we will attempt to study follows problem: 1) how to determine each node whether to enter sleep mode? 2) How long should a sensor be in the sleep state?

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