Adaptive Sensor Activation for Target Tracking in Wireless Sensor Networks

Jiming Chen, kejie Cao, Youxian Sun, Xuemin (Sherman) Shen
Date Submitted: 7 June 2009
Date Published: 11 June 2009

The final published version of this article is available at:
DOI: 10.1109/ICC.2009.5198708

Updated information and services can be found at:

These include:

Subject Classification  Vehicular Technology

Keywords  PID Control; Tracking; Sensor Network;

Comments  You can respond to this article at:
https://engine.lib.uwaterloo.ca/ojs-2.2/index.php/pptvt/comment/add/490/0

Copyright  ©2009 IEEE. Personal use of this material is permitted. However, permission to reprint/republish this material for advertising or promotional purposes or for creating new collective works for resale or redistribution to servers or lists, or to reuse any copyrighted component of this work in other works must be obtained from the IEEE.
Adaptive Sensor Activation for Target Tracking in Wireless Sensor Networks

Jiming Chen*, Kejie Cao*, Youxian Sun* and Xuemin (Sherman) Shen†
*State Key Lab. of Industrial Control Technology, Zhejiang University, Hangzhou, 310027 China
Email: jmchen@ieee.org, coollyfly@zju.edu.cn, yxsun@iipc.zju.edu.cn
†Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON N2L 3G1, Canada
Email: xshen@bcr.uwaterloo.ca

Abstract—This paper presents an adaptive sensor activation for target tracking in wireless sensor networks by dynamically adjusting the range of sensor selective activation instead of fixed one. A closed-loop control algorithm for the range of adaptive sensor activation is designed according to the online feedback of the tracking quality. The failed tracking case can also be handled by the proposed algorithm. Extensive simulation results show that the adaptive sensor activation achieves higher performance in terms of tracking effect and energy efficiency.

I. INTRODUCTION

Wireless sensor networks (WSNs) are networks consisting of several autonomous and compact nodes equipped with sensors that cooperatively monitor and record physical conditions at diverse locations [1][2]. The fast development of micro-fabrication has advanced the production of small and cheap sensors, which makes the WSNs become a hot research topic.

Cheapness and energy efficiency are the most two important requires for the sensors in WSNs [3]. Sensors in the WSNs should be deployed with both small and very large scales to instrument homes and highways, buildings and bodies, as well as to monitor and control defense applications, cheapness and smallness for the sensor are necessary. High energy efficiency, which means long sensor nodes’ working time, is also crucial since there is no energy recharge once sensors are deployed.

Many potential applications of WSNs, both civilian and military are developing rapidly. Target tracking is one of the most important applications [4]. There have been a lot of research works on target tracking in WSNs [5][6]. Most of works focus on two aspects: improving the accuracy of prediction algorithms, developing selective node activation algorithms that awaken sensors along the predicted path of the target from their sleeping mode. This paper focuses on the second aspect. An adaptive sensor activation algorithm is designed to advance the energy-quality tradeoff. The algorithm is designed according to the actual target maneuver, and the activated range can be adjusted automatically at each sampling period based on the feedback of tracking quality.

The remainder of this paper is organized as follows. Section II introduces some previous work on target tracking in WSNs. The assumptions and mobile target localization are described in Section III. Section IV proposes the adaptive sensor activation to advance the energy-quality tradeoff. Simulation results and detail comparisons are given in Section V, followed by the conclusion in Section VI.

II. RELATED WORK

Significant work has been done in the area of target tracking in WSNs. The following is a summary of main approaches.

A. Target Tracking in Smart Sensor Networks

Recently, research works on multi-functional and smart sensors have appeared, some of which can measure the angle between the target and sensor or the distance between them [7][8]. Xie et al use one smart sensor to measure the distance between the sensor and the target in one step, and predict and estimate the target’s state with EKF [8]. Wang et al choose three smart sensors which can measure the distance between target and sensor for the localization of target [9].

Although the smart sensors have their advantages, they are not suitable for deployment with high density because of the cost. In addition, smart sensors consume much more energy than binary-detection ones [8].

B. Tracking Moving Target with Binary-Detection Sensor Networks

Compared with smart sensors, binary-detection sensors are still superiority in many aspects: cheap, tiny, fault tolerance, and energy conservation.

Most appeared approaches use centroid localization for the simplicity, and S. Sundresh et al improve it. However, the improved algorithm needs high sample frequency which is difficulty for the cheap hardware like Mica2/MicaZ.

Some strategies with binary-detection sensor networks for target tracking like Naive Activation (NA), Randomized Activation (RA), Selective Activation (SA), Duty-cycled Activation (DA), etc. are proposed [10][11][12] to get better efficiency of energy consumption. S. Pattem et al consider the energy-quality tradeoff which means that the energy saving relying on the reducing of the detecting sensor nodes results in the decreasing in the tracking effect [10]. Compared with NA, RA and DA, the activation strategy SA obviously has the best balance between efficiency of energy and tracking effect. And the selective activation strategy is improved in this paper.
III. PRELIMINARY

A. Assumptions

In this paper, following assumptions are made for the system model: (1) time synchronization has been achieved in the network; (2) each sensor node has the same sense range; (3) the nodes can be self-localized; (4) centroid localization is used for the simplicity; (5) two different operation modes as tracking mode and sleeping mode are for each node.

The main notations used in the paper are listed in Table I.

<table>
<thead>
<tr>
<th>variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_s )</td>
<td>the radius of sense range</td>
</tr>
<tr>
<td>( R_a )</td>
<td>the radius of activated range</td>
</tr>
<tr>
<td>( X_a(t) )</td>
<td>the actual position of mobile target at time ( t )</td>
</tr>
<tr>
<td>( X_b(t) )</td>
<td>the measured position of mobile target at time ( t )</td>
</tr>
<tr>
<td>( Q_{me} )</td>
<td>the measured tracking quality</td>
</tr>
<tr>
<td>( Q_{re} )</td>
<td>the required tracking quality</td>
</tr>
<tr>
<td>( n_{sd} )</td>
<td>the number of sensors in tracking mode that detected the target</td>
</tr>
<tr>
<td>( n_{se} )</td>
<td>the number of sensors that can detect the target</td>
</tr>
<tr>
<td>( n_{sa} )</td>
<td>the number of the sensors that are activated in tracking mode</td>
</tr>
<tr>
<td>( K_p )</td>
<td>the proportion gain of PID algorithm</td>
</tr>
<tr>
<td>( T_d )</td>
<td>the differentiation gain of PID algorithm</td>
</tr>
<tr>
<td>( K_{re} )</td>
<td>the gain in recovery algorithm to get missing target</td>
</tr>
<tr>
<td>( K_{re} )</td>
<td>the gain for the reduction of the activated range</td>
</tr>
</tbody>
</table>

B. Problem Formulation

In strategy SA, the tracking progress is depicted in Fig.1. Define \( n_{se} \) as the number of sensor nodes that can potentially detect the target around the actual position \( X_a(t + 1) \). The nodes around \( X_a(t) \) are awaked to work in tracking mode and prepare for detecting the mobile target, the number of which is defined as \( n_{sa} \). However, only part of awaked nodes can detect the target, which means the nodes lying in the overlap of the two circles are able to detect the target. The number of these nodes is denoted as \( n_{sd} \). The new measured position \( X_b(t + 1) \) is obtained by finding the centroid of the location of these \( n_{sd} \) sensors in the overlap.

The target maneuver can be described with the state of position, velocity and acceleration [13]. It is thought that the acceleration of target is quite limited, which means that the change of velocity is slow during one sampling period. Therefore, the linear prediction can closely track the actual trajectory when the target runs with little acceleration [14]. Meanwhile, smaller activated range is expected to save more energy. On the contrary, when the acceleration is so large that the linear prediction can not track the target successfully, we hope the activated range can be enlarged to get better tracking quality. We propose an adaptive sensor activation algorithm to reduce the energy consumption. The algorithm can track the target successfully when the acceleration of mobile target is large, and improves the energy-quality tradeoff greatly when the acceleration is close zero.

IV. ADAPTIVE SENSOR ACTIVATION

A. PID Control for the Activated Range

PID control (P=proportion, I=integration, D=differentiation) is an efficient algorithm in closed-loop control system. The equation of the discrete PID algorithm is listed as blow:

\[
 u(t) = K_p \cdot [e(t) + \frac{T}{T_i} \sum_{j=0}^{t} e(j) + \frac{T_T}{T}(e(t) - e(t - 1))] \tag{1}
\]

where \( u(t) \) is the output of the controller, and \( e(t) \) is the error between expected value and measured value. \( T \) is the sampling time. \( K_p, T_i \) and \( T_d \) are the effective gains of proportion control, integration control and differentiation control, respectively.

The larger of \( K_p \), the more powerful of proportion control and the respond time of the control system would be faster. However, the system may be instable if the gain is too large. The effect of integration control is to decrease the system residue, which is not necessary in the tracking system. While the differentiation control reacts the tendency of the \( e(t) \).

In the dynamic tracking system, the activated range is changing with each sampling period, whose size of the next period is decided by the tracking quality in this period. We define the measured tracking quality \( Q_{me} \) as below:

\[
 Q_{me} = \frac{n_{sd}}{n_{se}} \tag{2}
\]

The larger the \( Q_{me} \) is, the better the tracking quality will be.

The \( e(t) \) in Eq.1 can be calculated as below:

\[
 e(t) = Q_{re}(t) - Q_{me}(t) \tag{3}
\]

where \( Q_{re}(t) \) is the required tracking quality of the system. If no more nodes working in tracking mode can detect the target as shown in Fig. 1, we can get better tracking quality from Eq.2. The average error \( e(t) \) that indexes tracking effect, will be decreased if \( n_{sd} \) is larger, which also means a better tracking effect will be achieved. Therefore, better required tracking quality means better required tracking effect. And we can set the required tracking quality to get expected tracking effect.
A simple feedback control framework with activated range can be depicted in Fig. 2. And the PD controller is adopted to design the algorithm, which is described in Eq.4

\[ u(t) = R_p(t) - R_p(t - 1) = K_p \cdot [e(t) + \frac{T_d}{T}(e(t) - e(t - 1))] \]

where \( R_p(t) \) is the radius of activated range at time \( t \), \( K_p \) and \( T_d \) are defined as the same in Eq.1.

The changing of \( R_p \) is based on the error between \( Q_{re} \) and \( Q_{me} \). When \( Q_{re} > Q_{me} \), which means the tracking quality is not as good as expected, the activated range will be enlarged. On the contrary, the activated range would be decreased if \( Q_{re} < Q_{me} \). Meanwhile, the value of \( R_p \) is according to the error of \( Q_{re} \) and \( Q_{me} \).

**B. Recovery Algorithm for Failed Tracking**

The controller of the feedback not only can adjust the activated range automatically but also can handle the situation of target missing and do the recovery to find the target again. When the tracking failed at time \( t \), which means the measured tracking quality is zero, we enlarge the activated range greatly at the predictive position at time \( t \). Exponential growth of the activated range is proposed in this paper:

\[ R_p(t+1) = \begin{cases} K_{en} \cdot D, & D \neq R_s \\ K_{en} \cdot R_p(t), & D = R_s \end{cases} \]

where \( n \) is the number of target’s consecutive missing. \( D \) is the distance between the predictive position at time \( t + 1 - n \) and the measured position at time \( t - n \). \( K_{en} \) is the gain to get tracked again.

For the situation \( D > R_s \), if the target misses for the first time, which means \( n \) is 1, the radius of activated range is enlarged more than \( D \) to make sure the actual point at time \( t + 1 \) falling into the activated range. In addition, we can adjust the gain \( K_{en} \) to enlarge the range. Considering both the energy consumption and tracking effect, we define \( K_{en} = 1.5 \). If \( D < R_s \), we take \( R_s / D \) instead of \( D / R_s \) to ensure the activated range increasing. If the sensors still can not find the target after enlarging the activated range, which means \( n \) increases to \( n + 1 \), the range would be enlarged exponentially to make sure the enlargement of activated range is faster than acceleration of mobile target.

Otherwise, the huge activated range would be decreased rapidly to save energy after the mobile target is found again at time \( t + 1 \). The decreased algorithm is just the opposite of Eq.5 as shown in Eq.6

\[ R_p(t + 2) = \begin{cases} K_{de} \cdot R_p(t + 1) \cdot \frac{n(R_s - D)}{R_p}, & D \neq R_s \\ K_{de} \cdot R_p(t + 1), & D = R_s \end{cases} \]

where \( K_{de} \) is the gain for the reduction of the activated range, which is defined as 2 to get better energy-quality trade off. The algorithm can be switched into PD control after getting the missing target again.

**V. EXPERIMENT RESULTS**

**A. Simulation Parameters**

In the actual process, the target may move straight or make turns, So the 180° turning track is considered in this paper on a \( 200m \times 200m \) area with sensors randomly deployed in a certain density, shown in Fig. 3. Other parameters are listed in Table II.

<table>
<thead>
<tr>
<th>( K_p )</th>
<th>( T_d )</th>
<th>( R_s )</th>
<th>( p )</th>
<th>( v_{s0} )</th>
<th>( Q_{re} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>0.6</td>
<td>4m</td>
<td>( \frac{\text{node/m}^2}{\text{znode/m}^2} )</td>
<td>10 m/s</td>
<td>0.6</td>
</tr>
</tbody>
</table>

The solid line is the actual trajectory, while the markers with \( \square \) are the sample points. The dashed circle is the range, in which the nodes can detect the target. The predictive position is depicted diamonds with dashdot circle around, which is the range of the activated sensors. And the dashed line marked with star is the measured trajectory.

The dashdot circle is keeping the same scope with dashed one at \( O-A \), because the trajectory is a line without acceleration, which makes the tracking quality quite admirable. However, when the target starts to turn its way at \( A-B \), which makes the tracking quality a little poor. The radius of the dashdot circle is getting much bigger than \( O-A \). Also the dashdot circle can turn back to the same with dashed one.
with a constant sensor activation based on PD control algorithm compared to 8.0m are taken to test the whole effect of the adaptive control again.

B. Tracking Effect of Adaptive Sensor Activation based on PD

Tracking executed. Therefore, a sudden enlarged dashdot circle happens at position $M$, and the missing target can be found again.

$$\rho = \begin{cases} \rho' & \text{if } R_s \geq 6.0 \\ \rho' & \text{if } 6.0 > R_s \geq 4.5 \\ \rho' & \text{if } 4.5 > R_s \geq 3.5 \\ \text{miss} & \text{if } R_s < 3.5 \end{cases}$$

$$\rho = \begin{cases} \rho' & \text{if } R_s \geq 6.0 \\ \rho' & \text{if } 6.0 > R_s \geq 4.5 \\ \rho' & \text{if } 4.5 > R_s \geq 3.5 \\ \text{miss} & \text{if } R_s < 3.5 \end{cases}$$

The relationship between the error and sense range is shown in Fig. 5. Combined with Fig. 4, it can be seen that better tracking effect (less error) is achieved for the adaptive sensor activation compared with SA when $sp=1.0$. When $sp=1.5$, tracking effect is much better, however, adaptive sensor activation could save much more energy with error around 1.0, which is quite acceptable for tracking effect. This also means adaptive algorithm can better balance for energy-quality tradeoff.

Furthermore, both the energy consumption curve and tracking error curve reach minimum when $R_s=3.5$ which is caused by some missing and recover algorithms.

C. Robust of Adaptive Sensor Activation based on PD Control in Tracking System

We apply different environmental parameters to test the robustness of the adaptive sensor activation based on PD control in tracking system: $\rho$ the density of sensors deployment in the area and $V_{ta}$ the velocity of the target.

1) Change of Sensor nodes’ density: Different $\rho$ are evaluated in this simulation experiment, and Fig. 6 shows the result. Generally, with high density of sensors deployment in the area, more nodes would be awaked to work in tracking mode. Therefore, more energy would be consumed for the situation that $\rho = \frac{1}{node/m^2}$ than $\rho = \frac{1}{2} node/m^2 \Rightarrow \rho \frac{1}{2} node/m^2$. On the other hand, the tracking precision can be enhanced with a large $\rho$, and the target tracking missing rate would be reduced sharply so that we can get more stable tracking effect as shown in Fig. 6. In this case, we can deploy sensors with certain density according to the sense range in order to get better tracking effect with less energy consumed.

2) Change of Target’s Velocity: We take the target’s velocity $V_{ta}$ of 5m/s, 10m/s and 15m/s for simulation. From Fig. 7, it is observed that the tracking effect decreases with

when the target moves straight with no acceleration again at B-E. Besides, we can clearly see that the target misses at position $M$, which start up the recovery algorithm for failed tracking executed. Therefore, a sudden enlarged dashdot circle happens at position $M$, and the missing target can be found again.

B. Tracking Effect of Adaptive Sensor Activation based on PD control

Experiments with different radius of sense range from 2.0m to 8.0m are taken to test the whole effect of the adaptive sensor activation based on PD control algorithm compared with a constant $R_p$. We use $P_t = n_s \cdot R_a^2$ as the energy consumption and define average Euclidean distance between the final estimated position and actual position as the tracking error[14]. We did the simulation 100 times and the average results are shown in Fig. 4 and Fig. 5.

Fig. 4 shows the relationship between energy consumption and sense range, and the tracking successful rates are also depicted. When the $sp$ (the ratio of $R_p$ and $R_s$) is 1.5, the target can be tracked successfully with ceratin rate if $R_s$ is between 2.6m and 3.6m. And when the $R_s$ is larger than 3.6m, the target can be tracked successfully. However, successful tracking is the precondition in the system design. Therefore, in order to tracking the target like that, we need to set the sense range around 4.0m to save energy. We can set the sense range around 5.0m and 6.0m when $sp$ is 1.2 and 1.0, respectively. So, we have to set different values of $sp$ for different targets to make sure tracking successfully. However, the adaptive sensor activation algorithm solves the problem primely that the tracking successful rate keeps to 100% whatever the sense range is.

Meanwhile, the energy consumption is perfect:

- $R_s \geq 6.0$ : We would set the $sp=1.0$, the energy consumption of adaptive algorithm is close to that of $sp=1.0$.
- $6.0 > R_s \geq 4.5$: We would set the $sp=1.2$, the energy consumption of adaptive algorithm is much less than that of $sp=1.2$.
- $4.5 > R_s \geq 3.5$: We would set the $sp=1.5$, the energy consumption of adaptive algorithm is much less than that of $sp=1.5$.
- $R_s < 3.5$: The target can be tracked successfully with adaptive algorithm, and the energy consumption fluctuates a little around the consumption when $R_s=3.5$ which is caused by some missing and recover algorithms.
The tracking effect with different $\rho$

![Fig. 6. The tracking effect with different $\rho$](image)

The tracking effect with different $V_{ta}$

![Fig. 7. The tracking effect with different $V_{ta}$](image)

the increment of $V_{ta}$. Meanwhile, the larger error needs larger predictive scope to awaken more sensors in one step. So the average energy consumption in each step is much more predictable scope to awaken more sensors in one step. So the average energy consumption for a given distance is uncertain because speedy target needs less sample steps. To get the speedy target neatly, we need larger sense range or deploy the sensors more densely to cover just one sudden turning along the trajectory of the mobile target, which can efficiently save energy.

For our future work, we will consider extended Kalman Filter to predict the state of mobile target instead of linear trajectory prediction, which may improve the tracking effect. In addition, some disturbances such as transmission error or measure error of some sensors will be considered. Randomized activation or probabilistic activation combined with selective activation can also be considered to save more energy.

ACKNOWLEDGEMENT

This work is partially supported by NSFC-Guangdong joint Project under grants U0735003; NSFC under grants No.60604029, 60702081; NSF of Zhejiang Province under grants No.Y106384; and 863 high-tech Project 2007AA041201.

REFERENCES


