A Flexible Boundary Sensing Model for Group Target Tracking in Wireless Sensor Networks

Quanlong Li, Zhijia Zhao, Xiaofei Xu, and Qingjun Yan

School of Computer Science and Technology, Harbin Institute of Technology, Harbin, P.R. China, 150001 liquanlong@hit.edu.cn

Abstract. Group target usually covers a large area and is more difficult to track in wireless sensor networks. In traditional methods, much more sensors are activated and involved in tracking, which causes a heavy network burden and huge energy cost. This paper presents a Boundary Sensing Model (BSM) used to discover group target's contour, which conserves energy by letting only a small number of sensors – BOUNDARY sensors participate in tracking. Unlike previous works, the proposed BSM is flexible by adjusting the boundary thickness thresholds. We analytically evaluate the probability of becoming a BOUNDARY sensor and the average quantity of BOUNDARY sensors, which proved to be affected by communication radius, density, and boundary thickness thresholds. Extensive simulation results confirm that our theoretical results are reasonable, and show that our proposed BSM based group target tracking method uses less number of sensors for group tracking without precision loss.

Keywords: Sensor Networks, Sensing Model, Boundary Sensing Model, Group Target Tracking.

1 Introduction

A group target is a set of individual targets moving coherently.As the targets move closely with each other, it is unpractical or unnecessary to localize every specific target in wireless sensor networks, especially when the scale of the group is relatively large (e.g. motorcade, tank column, or a herd of buffalos). In traditional methods, all discovering sensors are involved in tracking. With group target's scale increasing, the network burden and energy cost will be rather considerable. In this paper, we devise a flexible boundary sensing model to discover the group target's contour, in which only a small part of discovering sensors ar[e in](#page-11-0)volved in tracking and the tracking sensors' quantity is adjustable by some customized parameters.

The target tracking problem in WSNs has been a topic of extensive study under different metrics and assumptions [2-4,7]. However, most of them focused on individual target tracking [1-3].For group target tracking [6], some irradiative ideas of tracking targets through boundary detection are proposed in prior work [1, 5, 8]. The authors in [8] consider targets and events of interest are presented in a region, and

© Institute for Computer Sciences, Social Informatics and Telecommunications Engineering 2012

Joel J.P.C. Rodrigues et al.: (Eds.): GreeNets 2011, LNICST 51, pp. 25–36, 2012.

devise a region-based evolving targets tracking algorithm. A problem of contour tracking had been studied in [1], in which the boundaries of blobs of interest were tracked and topological changes were captured.

In this paper, we make the following contribution. We map the group target boundary sensing problem to the test of whether a sensor's Discovering Neighbors Ratio is within its thresholds. Based on our mapping, we use tool of Geometric Probability to analytically evaluate the probability of a sensor becomes a boundary sensor and the average number of boundary sensors.

Our formulations show that the boundary thickness is independent of the sensor's sense radius, and depends on the sensors' density and communication radius. Further, given a sensor deployed in a monitoring area, its probability of becoming a boundary sensor only depends on the boundary thickness thresholds. Based on these analysis results, the formulation to calculate the average number of boundary sensors is given.

The rest of this paper is organized as follows: Section 2 describes the setup of Boundary Sensing Model. In section 3, we analyze BSM theoretically. And some useful formulations are also given in this section. Section 4 states a group target tracking scheme based on BSM. The validation of our theorectical results and simulation of group target tracking are shown in Section 5. We summarize our work in Section 6.

2 Boundary Sensing Model (BSM) Setup

In [1], the authors designed a simple method to detect continuous object's boundary, but the thickness of boundary is fixed. In this section, a more flexible sensing model called Boundary Sensing Model (BSM) is proposed, where the thickness of boundary is adjustable.

The model is built upon the binary sensing model [2,3], which is famous for its minimal requirement about sensing capabilities and ease to extend other kinds of sensors. In binary sensing model, sensors are placed in two categories: discovering sensors (output 1) and non-discovering sensors (output 0). We denote this character as d*iscovering status* (*DS*).

Definition 1. *Discovering neighbors ratio* (*DNR*). *Given sensors set I and sensor i, let* $\Theta(i)$ *be i's neighbors set and* $\Phi(i)$ *be a set in which the elements are i's neighbors discovering target (named discovering neighbors). Then i's discovering neighbors ratio is defined as*

$$
\eta: I \to [0,1]
$$

\n
$$
\eta(i) = \frac{|\Phi(i)|}{|\Theta(i)|}, \text{ for all } i \in I
$$
\n(1)

where $|A|$ *denotes the elements number in set* A .

DNR describes the ratio of a sensor's discovering neighbors to its total ones. There is a *neighbors table* in each sensor, where its neighbors' DS is stored, as shown in Table 1. Through looking up the table, DNR can be calculated.

Neighbors' ID	DS
25	
27	
34	
. .	.
23	

Table 1. Neighbors table

According to formula (1), *boundary status* can be defined as:

Definition 2. *Boundary status (BS). Given sensor i,i* \in *I*, *i's boundary status is defined as:*

$$
\chi: I \to \{INNER, BOUNDARY, OUTER\},
$$

\n
$$
\chi(i) = \begin{cases}\nOUTER, \eta(i) \le H_0, \\
BOUNDARY, \ H_0 < \eta(i) < H_1, \text{ for all } i \in I. \\
INNER, \ \eta(i) \ge H_1.\n\end{cases}
$$
\n
$$
(2)
$$

where H₀ and H₁, $0 \leq H_0 \leq H_1 \leq 1$ *are parameters to adjust the thickness of boundary. The BS describes whether one sensor is on the boundary of a region which contains a group target. When H₀ =0 and H₁=1, the set of all BOUNDARY sensors is named Max BOUNDARY Sensors Set, denoted as* $\mathcal{B}, \mathcal{B} \subseteq I$ *; otherwise, it's named as Adjustable BOUNDARY Sensors Set, denoted as B,* $B \subseteq B \subseteq I$ *.*

Definition 3. *Boundary sensing model* (*BSM*): *The boundary sensing model is a sensing model, in which every sensor can compute its BS by communicating with its neighbors.*

Figure 1 illustrates a scene of a group target appearing in a region deployed with numerous BSM sensors.

Fig. 1. A group target in BSM sensor networks

Every sensor is in the OUTER status initially. Once the signal strength of events it captured exceeds a certain threshold, the sensor turns into discovering status. Meanwhile, it also has a responsibility of notifying its neighbors to update their neighbors tables. Based on the updated neighbors table, a sensor could calculate its DNR and decide which BS it will become. There are three different of situations: i) if DNR≤H0, it gets into the OUTER status; ii) if DNR≥H1, it gets into the INNER status; iii) otherwise, it gets into the BOUNDARY status. The whole process is completely distributed, and only needs local communication among sensors. In Figure 2, boundary status transition diagram is shown. We assume there isn't any transition between INNER and OUTER. As the target moves continuously, it is feasible by adjusting sensor networks' parameters, such as sensors density.

Fig. 2. Boundary status transition diagram

3 Analysis of BSM

We assume that *N* sensors are identically and independently distributed within a planar area, according to a random (uniform) distribution with the density of ρ . And every sensor has the same communication radius R_{comm} and the same sense radius *R*_{sense}. We define *d* as the average distance between two sensors. To ensure a sensor can communicate with its neighbors, we assume that $R_{\text{comm}} > d$.

First, we analyze boundary thickness using the number of sensors as it's metric. We define the sense line as a vertical line with a distance of R_{sense} to the targets area line, as illustrated in Figure 3.

Fig. 3. A scheme for Boundary thickness analysis

Theorem 1: *Given a Max BOUNDARY Sensors Set , sensor communication radius* R_{sense} and sensors density ρ , the boundary thickness of β is given by

$$
T_{\text{Boundary}} = 2 \times \left[\frac{R_{\text{comm}}}{\sqrt{1/\rho}} \right], \quad R_{\text{comm}} > \sqrt{1/\rho} \tag{3}
$$

Proof: *Since R_{comm}* > *d*, the two closest sensors on either side of the sense line must be *BOUNDARY sensors, as the sensor 2 and sensor 3 shown in Figure 3. Further, we can find such a rule.*

$$
T_{\text{Boundary}} = \begin{cases} 2, & d \le \text{Rcomm} < 2d \\ 4, & 2d \le \text{Rcomm} < 3d \\ 6, & 3d \le \text{Rcomm} < 4d \\ \dots \end{cases} \tag{4}
$$

from which we can conclude that

$$
T_{\text{Boundary}} = 2 \times \left[\frac{R_{\text{comm}}}{d} \right] = 2 \times \left[\frac{R_{\text{comm}}}{\sqrt{1/\rho}} \right], \quad R_{\text{comm}} > \sqrt{1/\rho} \tag{5}
$$

In Figure 3, we note that the sense line's location is used to analyze boundary thickness, without considering of *R*_{sense}.

Lemma 1: *Given sensor i, i* \in β *, let* η *(i) be sensor i's discovering neighbors ratio. Then we must have*

$$
\eta(i), \ \eta(i) \in Y = \{\frac{1}{|\Theta(i)|}, \frac{2}{|\Theta(i)|}, \cdots, \frac{|\Theta(i)| - 1}{|\Theta(i)|}\}\tag{6}
$$

is a discrete random variable, and the probability that it takes on each value is given by

$$
Pr(\eta(i) = \frac{1}{|\Theta(i)|}) = Pr(\eta(i) = \frac{2}{|\Theta(i)|}) = \cdots
$$

=
$$
Pr(\eta(i) = \frac{|\Theta(i)| - 1}{|\Theta(i)|}) = \frac{1}{|\Theta(i)| - 1}
$$
 (7)

Proof: *Since sensor i is uniformly distributed over interval [a, b], as shown in Figure 4. It follows that*

 $Pr(i \text{ in } [a, c]) = Pr(i \text{ in } [c, b]) = 0.5$

Then $\forall j \in \Theta(i)$, we must have

$$
Pr(j \text{ in } [a, c]) = Pr(j \text{ in } [c, b]) = 0.5
$$

And it follows that $Pr(DS(j) = 0) = Pr(DS(j) = 1) = 0.5$. *According to Definition I*, $∀i ∈ B$, we have

$$
\eta(i) = \frac{|\Phi(i)|}{|\Theta(i)|} = \frac{\sum_{j=1}^{|\Theta(i)|-1} DS(j)}{|\Theta(i)|}, \ j \in \Phi(i)
$$
\n(8)

By discrete random variable's operation, we can conclude that

$$
Pr(\eta(i) = \frac{1}{|\Theta(i)|}) = Pr(\eta(i) = \frac{2}{|\Theta(i)|}) = \cdots
$$

=
$$
Pr(\eta(i) = \frac{|\Theta(i)| - 1}{|\Theta(i)|}) = \frac{1}{|\Theta(i)| - 1}
$$
 (9)

Fig. 4. Analysis of discovering neighbors ratio

Theorem 2: *Given sensor i, i* \in *B*, let H_0 and H_1 be η (*i*) *s* thresholds, then the *probability that sensor i is a BOUNDARY sensor is given by*

$$
Pr(BS(i) = BOUNDARY) = \sum_{H_0 \ll \eta(i) \ll H_1} \frac{1}{|\Theta(i)| - 1}, \eta(i) \in Y
$$
\n(10)

Proof: *Based on the Definition 2 and Lemma 1, the conclusion is obvious.*

Assuming group target's perimeter Lgroup target is long enough, we consider the BOUNDARY sensors constitute a curving band with the same length of outer and inner cures. Then a Max BOUNDARY Sensors Set's size can be computed by the following LEMMA.

Lemma 2: Given a Max BOUNDARY Sensors Set β , then its average size is given by

$$
|\overline{\mathcal{B}}| = \frac{L_{\text{group target}} \times W_{\text{Boundary}}}{\sqrt{1/\rho}}
$$
 (11)

where $L_{group\ target}$ *is group target's perimeter,* $W_{Boundary}$ *is boundary thickness, and* ρ *is the density of sensors.*

Proof: *Given a unit length of group target's boundary, the average number of sensors in this area can be calculated by W_{Boundar}/d, where d is the average distance between two sensors. Since* $d = (1/\rho)^{1/2}$, then we can conclude that

$$
|\overline{B}| = L_{\text{group target}} \times \frac{W_{\text{Boundary}}}{d} = \frac{L_{\text{group target}} \times W_{\text{Boundary}}}{\sqrt{1/\rho}}
$$
(12)

Theorem 3: *Given sensor i, i* \in *B*, let H_0 and H_1 be η (*i*) *s* thresholds, then the *average size of Adjustable BOUNDARY Sensors Set B is given by*

$$
\frac{2L_{\text{group target}} \times \left[R_{\text{comm}} / \sqrt{1/\rho}\right]}{\sqrt{1/\rho}} \times \sum_{H_0 < \eta(i) < H_1} \frac{1}{\pi R_{\text{comm}}^2 \rho - 1},
$$
\n
$$
\overline{\eta(i)} \in Y' \quad \text{where } Y' = \{\frac{1}{|\Theta(i)|}, \frac{2}{|\Theta(i)|}, \dots, \frac{|\Theta(i)| - 1}{|\Theta(i)|}\}\tag{13}
$$

Proof: *According to Theorem 1, Theorem 2 and Lemma 2, we can conclude that*

$$
\overline{|B|} = \sum_{i=1}^{|\overline{B}|} Pr(BS(i) = BOUNDARY)
$$
\n
$$
= |\overline{B}| \times Pr(BS(i) = BOUNDARY)|_{i \in \mathcal{B}} = |\overline{B}| \times \sum_{H_0 \lhd \eta(i) < H_1} \frac{1}{|\Theta(i)| - 1}
$$
\n
$$
= \frac{L_{\text{group target}} \times T_{\text{Boundary}}}{\sqrt{1/\rho}} \times \sum_{H_0 \lhd \eta(i) < H_1} \frac{1}{\pi R_{\text{comm}}^2 \rho - 1}
$$
\n
$$
= \frac{2L_{\text{group target}} \times \left(R_{\text{comm}} / \sqrt{1/\rho}\right)}{\sqrt{1/\rho}} \times \sum_{H_0 \lhd \eta(i) < H_1} \frac{1}{\pi R_{\text{comm}}^2 \rho - 1}, \quad \overline{\eta(i) \in Y}
$$
\n(14)

where $\overline{Pr(BS(i) = BOUNDARY)}$ $i \in B$ *is the average probability that sensor* $i, i \in B$ *is a BOUNDARY sensor, and* $\overline{|\Theta(i)|}$ *is the average number of sensor i's neighbors.*

4 Group Target Tracking Based on BSM

Based on our proposed BSM, a divide-merge group target tracking method is stated in this section.

In this method, the group tracking process is separated into two steps – boundary dividing and boundary merging. In the first step, the sensors that discover the boundary of a group target are divided into multiple clusters, and each cluster is responsible for tracking a partial boundary of the group target. In each cluster, there is a cluster head (CH) which gathers information from its cluster members (CM) and aggregates these data to form a local convex hull. Then, the aggregated data is sent back to the sink which is usually monitored by humans. In the second step, when sufficient information of local convex hulls is collected at the sink, it will execute the merging algorithm to combine those convex hulls into a global convex hull which is considered as the whole contour of the group target.

Fig. 5. Illustration of the divide-merge group target tracking method

When a group target is moving, some previously constructed clusters are destroyed and some new ones will be formed. In order to track the group target continuously, clusters must be maintained so that out-of-date clusters are eliminated and new clusters are dynamically created. Consider a newly formed cluster. As group target moving, some new sensors will join the cluster. Meanwhile, some old ones quit. So the topology of the cluster is changing and the original CH may not be able to continue playing as a cluster head. Here, we choose the sensor closest to the cluster's center as the new CH.

In Figure 5, the process of group target tracking based on BSM is illustrated. We note that several partial boundaries combine the whole boundary of group target.

5 Simulation and Verification

5.1 Simulation Setup

In the simulation, BSM sensors are randomly scattered with a uniform distribution in the monitoring region which is a rectangle area with the size of $200m \times 175m$. The communication radius and sense radius are changed according to the deployment density of sensors to guarantee enough coverage of the monitoring region.

A group target contained 400 individuals is simulated at the speed of $5m/s$. If there is any individual target gets into one sensor's circle whose radius is R_{energy} , the sensor will discover it without knowing the number of targets or their precise positions.

6 Impact Factors of Boundary Thickness and Tracking Sensors' Quantity

Based on the theoretical analysis in Section 3, we made a great deal of experiments on the factors that impact on boundary thickness.

Figure 6 illustrates the impaction of H_0 and H_1 . With the difference between H_0 and H_1 getting smaller, the boundary thickness is getting thinner accordingly. This is reasonable according to Theorem 3.

The impaction of communication radius R_{comm} on boundary thickness is given in Figure 7. We can find the boundary thickness broadens with R_{comm} increasing. This is because a sensor has more neighbors, and then it has bigger chance to become a BOUNDARY sensor. Theorem 1 predicts the trend.

Fig. 6. Boundary thickness changes by vary H0 and H1

Fig. 7. Boundary thickness changes by vary Rcomm

Fig. 8. Comparison between practical and theoretical boundary thickness

Fig. 9. Comparison between practical and theoretical BOUNDARY sensors' quantity

Fig. 10. Comparison between BSM based tracking sensors' number and the one that all discovering sensors are involved in tracking

In Figure 8 and Figure 9, the comparisons between practical and theoretical results are illustrated, from which it is obvious that our theoretical results are closed to the practical situation.

In Figure 10, the tracking sensors' quantities comparison between BSM based tracking (BSM tracking) and tracking involved all discovering sensors (ALL tracking) is illustrated. With the expanding of group target's scale, the tracking sensors number increases faster in ALL tracking; While in BSM tracking, the number does not increase significantly. The reason is that the number of tracking sensors varies directly with the group target's area in ALL tracking, and varies directly with the group target's perimeter in BSM tracking.

7 Tracking Performance

In Figure 11, keeping the difference between H_0 and H_1 fixed, we can find the boundary become tighter with H_0 and H_1 increasing. The reason is that when H_0 and H_1 increase, some INNER sensors closed to the boundary turn into BOUNDARY sensors, while some outer BOUNDARY sensors turn into OUTER sensors. As a result, it's helpful to make H_0 and H_1 a little higher. However, if the H_0 and H_1 turn too high, the localization result may be smaller than the real contour.

Fig. 11. H0 and H1 s impactions on localization precision

8 Conclusion

In this paper, we suggested a boundary sensing model - BSM used for group target tracking. We mapped the boundary sensing problem to the test of whether a sensor's discovering neighbors ratio is within boundary thickness thresholds. And we derived analytical expressions for the probability that a sensor turns into a BOUNDARY sensor. After the sensor network is deployed uniformly, we showed that the number of tracking sensors in BSM only depends on our proposed thresholds. Through simulation, we verified our theoretical results and confirmed our proposed group target tracking method based on BSM eliminates the tracking sensors' quantity significantly under the premise of precision.

References

- 1. Zhu, X., Sarkar, R., Gao, J., Mitchell, J.S.B.: Light-weight Contour Tracking in Wireless Sensor Networks. In: Proceedings of IEEE INFOCOM 2008, pp. 1849–1857 (2008)
- 2. Aslam, J., Butler, Z., Constantin, F., Crespi, V., Cybenko, G., Rus, D.: Tracking a Moving Object with a Binary Sensor Network. In: ACM Sensys 2003, Los Angeles, California, USA, pp. 150–161 (2003)
- 3. Shrivastava, N., Mudumbai, R., Madhow, U., Suri, S.: Target tracking with binary proximity sensors: Fundamental limits, minimal descriptions, and algorithms. In: Proceedings of ACM SenSys (2006)
- 4. Chen, W., Hou, J.C., Sha, L.: Dynamic clustering for acoustic target tracking in wireless sensor networks. IEEE Transactions on Mobile Computing 3(3), 258–271 (2004)
- 5. Ji, X., Zha, H., Metzner, J.J., Kesidis, G.: Dynamic Cluster Structure for Object Detection and Tracking in Wireless Ad-Hoc Sensor Networks. In: IEEE International Conference on Communications, ICC 2004, Paris, France, June 20-24 (2004)
- 6. Cao, D., Jin, B., Cao, J.: On Group Target Tracking with Binary Sensor Networks. In: Proceedings of the 5th IEEE International Conference on Mobile Ad Hoc and Sensor System, MASS, pp. 334–339 (2008)
- 7. Gui, C., Mohapatra, P.: Power Conservation and Quality of Surveillance in Target Tracking Sensor Networks. In: Proc. of the 10th Annual International Conference on Mobile Computing and Networking, pp. 129–143 (September 2004)
- 8. Jiang, C., Dong, G., Wang, B.: Detecting and Tracking of Region-based Evolving Targets in Sensor Networks. In: IEEE ICCCN 2005, San Diego, California (2005)