J Supercomput (2010) 51: 131–148
DOI 10.1007/s11227-009-0278-5

Designing energy efficient target tracking protocol with quality monitoring in wireless sensor networks

Minyi Guo · Elizabeth Olule · Guojun Wang · Song Guo

Published online: 29 April 2009

Abstract Target tracking is one application of wireless sensor networks and energy efficient target tracking algorithms that can be used for accurate tracking are highly desired. In order to achieve energy savings, we focus on reducing energy usage by limiting the number of sensors used to track a target through monitoring their data quality and by limiting the amount of data being sent to the cluster head. We propose an energy efficient target tracking protocol that uses two algorithms to accomplish this goal. Simulation studies show that the network lifetime is extended up to 35% with application of both algorithms and that the side effect on target tracking accuracy is not too negative.

Keywords Wireless sensor networks · Target tracking · Energy efficiency · Network lifetime · Data quality

M. Guo
School of Information Engineering, Dalian Maritime University, Dalian, Liaoning 116026, China
e-mail: guo-my@cs.sjtu.edu.cn

M. Guo
e-mail: minyi@u-aizu.ac.jp

E. Olule
VAS Planning, Network Group, MTN Uganda, P.O. Box 24624, Kampala, Uganda
e-mail: olulee@mtn.co.ug

G. Wang (✉)
School of Information Science and Engineering, Central South University, Changsha 410083, China
e-mail: csgjwang@gmail.com

S. Guo
School of Computer Science and Engineering, The University of Aizu, Aizu-Wakamatsu City, Fukushima 965-8580, Japan
e-mail: sguo@u-aizu.ac.jp

1 Introduction

One of the applications that is greatly benefiting from sensor technology is target tracking and is used in both military and commercial applications [1].

Energy efficiency is a very important aspect of target tracking protocols and the strategies for saving energy in wireless sensor networks fall into two categories: those used at individual sensor level and those for groups of sensors. At the individual sensor level, we can either shutdown the devices when they are not in use, i.e., Dynamic Power Management (DPM) [2] or adjust the power being used to match the workload, i.e., Dynamic Voltage Scheduling (DVS) [3]. At individual sensor level, it is common to put the sensor in sleep mode to conserve energy.

For groups of sensors, in order to reduce energy used by the group, we can reduce the data in communication [4], reduce the frequency of communication [5], and reduce the number of sensors in the group, for example, by using prediction [6]. Balancing energy usage in the network is another method of minimizing energy use and one way of performing this is by use of mobile sinks [7].

We propose an energy efficient target tracking protocol that reduces energy consumption by reducing the number of sensors involved in tracking the target and also by reducing the amount of data being sent to the cluster head. We have published our preliminary work in [8] where we propose a target tracking protocol that uses two algorithms: RARE-Area (Reduced Area REporting) and RARE-Node (Reduction of Active Node REdundancy). The RARE-Area algorithm reduces the number of sensors used for tracking by monitoring the data quality. The algorithm allocates a weight to the sensor data and only sensors whose weight value is above the set threshold are allowed to participate in tracking. The RARE-Node algorithm reduces the amount of redundant data in the network by considering the spatial relationship between neighboring sensors. Simulation studies show that application of our protocol gives significant energy savings and does not have too much of a negative impact on the tracking accuracy.

2 Related work

Target tracking protocols use different ideas that allow a target to be tracked successfully through a sensor network. One idea focuses on determining which sensors should be used to track the target, for example, by using the perceived value or actual value of the sensor data.

Protocols which use the perceived value of a sensor's information usually decide in advance the value of a sensor's data and then determine whether the sensor should participate in tracking or not. In many cases, the perceived value of a sensor data is proportional to the distance between the sensor and the target. In [9], the cluster head selects sensors nearest to the predicted path for tracking. In [10], the authors consider tracking mobile targets with a certain Quality of Monitoring (QoM) while considering coverage. They use a virtual sensing range in their scheme together with a Quality of Monitoring factor and the next sensor to take over tracking is usually close to the predicted target path. In [11], the authors propose a mechanism to predict the probability that a sensor's information will be useful and use it to decide whether the sensor should participate in tracking or not. Two measures of information utility proposed are the Mahalanobis distance measure and measures of expected posterior distribution and these measures use the perceived value of the sensor data. In [12], the authors also introduce an information utility measure to select which sensors to query and to dynamically guide data routing.

For protocols that use the actual value of the sensor data, the protocols allow the sensors to gather data and then determine which data will be used for tracking, i.e., tracking based on the sensor data quality. In [11], one of the information utility measures requires data from the sensor before it can decide the usefulness of the data. In [8], only sensors with a quality of data higher than the set threshold are allowed to participate in tracking.

One method of conserving energy is by reducing the amount of data being transmitted in the network, for example, by reducing the amount of redundant data being transmitted. The aspect of data redundancy is not mentioned in many cases, but in [10] they address this issue by trying to ensure that the distance between the current duty sensor and the next duty sensor is at least twice the virtual sensing range. In [13], the authors analyze the problem of estimating redundant sensing areas among neighboring wireless sensors.

For our algorithms, we limit the number of nodes participating in tracking by using a hybrid method of the actual and perceived value of the sensor data and limit the amount of redundant data in the network.

3 RARE algorithms

Our research looks at developing an energy efficient target tracking protocol that minimizes total energy used for tracking by minimizing total communication energy. Communication energy used is minimized by reducing the number of sensors involved in tracking by monitoring data quality and by reducing the number of data transmissions to the cluster head.

3.1 Assumptions

1. Each sensor knows its location and the location of its neighbors.
2. The sensor network is homogeneous.
3. The sensors are all clock synchronized.
4. Sensors are randomly distributed in the network in a two-dimensional plane.
5. The target being tracked is single and finite.

3.2 Target localization and beacons

In order to determine the target position, we use trilateration [14] which requires three range measurements to determine the target position. The range information is obtained from received signal strength measurements and a sensor uses two other range measurements from its neighboring sensors who are also tracking the target.

Beacons are used to distribute the range measurement information between sensors and are periodically broadcast from sensors that are participating in tracking to their neighbors.

3.3 Operation of algorithms

The operation of the algorithms is as follows:

Step 1: When a target is first detected by a sensor, it continues operating in the normal mode as it takes n measurements so that the initial errors and delay in getting results for tracking are reduced.

Step 2: The RARE-Area algorithm is run and uses some of the measurements to calculate the weight W for the data indicating the quality of data at that sensor at that time. At least three measurements are required to determine the range and the target motion status. If the calculated weight $W \geq W_U$, the weight threshold, then the data from that sensor can be used for tracking and this sensor sends beacons to its neighbors and waits to receive at least two other beacons. Once a sensor has received at least two beacons, the trilateration algorithm uses the beacon data to estimate the target position. If the RARE-Node algorithm is not being used, the sensor then sends its data to the cluster head. If RARE-Node is being used, then go to step 3.

Step 3: We run the RARE-Node algorithm to determine whether the sensor data is redundant or not. If the data is redundant, it is not sent to the cluster head, otherwise it is sent to the cluster head by the responsible node.

The weight threshold W_U determines the minimum quality of data to be used for tracking the target and is set on configuring the network. As the target travels through the sensing field, the nodes periodically recalculate the weight W and monitor the data quality at each sensor so that only nodes with the required quality of data participate in tracking.

3.4 RARE-Area algorithm

The purpose of the RARE-Area algorithm is two fold. First, it limits the number of sensors participating in tracking, and secondly it controls the amount of data to be transmitted to the cluster head under certain conditions. It achieves these two goals using a weighting scheme to allocate a value to the sensor data, indicating the quality of data at the sensor at that time. As the distance between the target and the sensor increases, the strength of the signal decreases [15], and if we assume a fairly constant level of noise in the sensing area, this means that as the target distance increases, the percentage of noise in the received signal increases. We loosely define quality as the percentage of noise within the received target signal. In our work, we limit the number of sensors being used for tracking according to the quality of data. Low quality data contains a higher percentage of noise in it because the target is far away from the sensor. In our preliminary work in [8], the quality of data was determined by three factors: target distance, target direction of motion, and target velocity. In this work, we use two factors: target distance and target motion status.

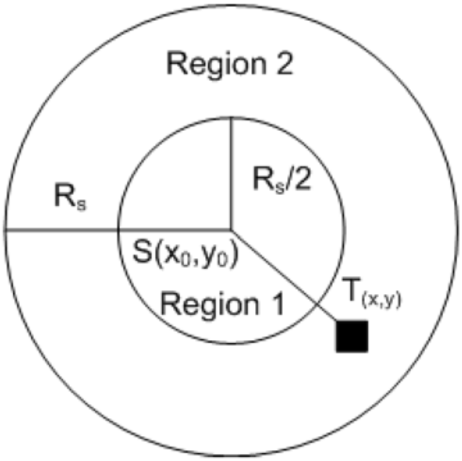


Fig. 1 Sensing region s

Distance factor. We use the target distance as an approximate indicator of the signal quality. The distance factor α_d represents the quality of the signal or data received. We use a zero mean Gaussian with standard deviation of 1 to represent our distance factor α_d, so:

$$\alpha_\mathrm{d} = \frac{1}{\sqrt{2\pi}} e^{-\frac{d_\mathrm{t}^2}{2R_\mathrm{s}^2}}, \tag{1}$$

where d_t is the distance to the target and R_s is the sensor normal sensing range. For α_d, we consider two regions in the sensing range as illustrated in Fig. 1. Sensor $S(x_0, y_0)$ and the target $T(x, y)$ are separated by a distance d_t.

The two regions are defined as Region 1 where $d_\mathrm{t} < \frac{R_\mathrm{s}}{2}$ and Region 2 where $\frac{R_\mathrm{s}}{2} \leq d_\mathrm{t} \leq R_\mathrm{s}$.

In our model, we assume that if the target is in Region 1, the data is automatically high quality and so the final distance factor becomes:

$$\alpha_\mathrm{d} = \begin{cases} W_U & d_\mathrm{t} < \frac{R_\mathrm{s}}{2} \\ \left(\frac{1}{\sqrt{2\pi}}\right) e^{-\frac{d_\mathrm{t}^2}{2R_\mathrm{s}^2}} & \frac{R_\mathrm{s}}{2} \leq d_\mathrm{t} \leq R_\mathrm{s}. \end{cases} \tag{2}$$

Motion factor. The target motion status is the second factor we consider in our weighting algorithm. When looking at the motion status, we consider two categories of motion, either the target is moving or it is stationary. In order to determine the motion status, we compare the target distance d_t at time t and target distance $d_{t+\delta t}$ at time $t + \delta t$. We assume that for that short time interval, the target velocity and direction of motion are constant in order to determine target motion status we assume the following

(i) If $d_t > d_{t+\delta t}$, or $d_\mathrm{t} < d_{t+\delta t}$, target is Moving.
(ii) If $d_t = d_{t+\delta t}$, target is Stationary.

We define the motion factor $\alpha_m(m, s)$ (or motion factor ratio) as the degree of importance attached to different types of target motion. The values allocated to m and s are the relative weights given to a target when it is in motion and stationary respectively. So, for a moving target:

$$\alpha_m(m, s) = m \tag{3}$$

and for a stationary target:

$$\alpha_m(m, s) = s. \tag{4}$$

Weighting system. In the final weighting scheme, sensors nearer to the target receive a higher weighting than sensors further away from the target and the weighting is also affected by the target motion status. If the target is stationary, then the data at the sensor is given a lower weight. The final weight W is given by:

$$W = \begin{cases} W_U & d_\mathrm{t} < \frac{R_\mathrm{s}}{2} \\ \left(\frac{\alpha_m(m,s)}{\sqrt{2\pi}}\right) e^{-\frac{d_\mathrm{t}^2}{2R_\mathrm{s}^2}} & \frac{R_\mathrm{s}}{2} \le d_\mathrm{t} < R_\mathrm{s}, \end{cases} \tag{5}$$

where W_U is the weight threshold whose value is determined from experiments and depends on the sensing range and width of Region 2, $\alpha_m(m, s)$ is the motion factor with ratio m:s for target in motion and stationary target, respectively, d_t is the distance to the target, R_s is the sensing range. The motion factor is determined by the network operator.

3.5 RARE-Node algorithm

The RARE-Node algorithm determines whether the data generated by a node is redundant or not. When the RARE-Node algorithm is run on a node, it first checks for any neighboring sensors within its sensing range. If no sensor is found, then the data is not redundant and is forwarded to the cluster head. If neighboring sensors exist, the RARE-Node algorithm selects the nearest one to the target and checks whether that neighbor has enough energy to send data to the cluster head or not. If it has enough energy, then the sensor determines which of them (itself or that nearest neighbor) is responsible for sending the data to the cluster head by considering the spatial relationship between them.

If the nearest neighbor does not have enough energy to transmit data to the cluster head, then the RARE-Node algorithm checks the energy of the next nearest neighbor to the target until it finds one with enough energy to transmit data to the cluster head.

In order to determine data redundancy, we assume each sensor has a disc shaped sensing range with radius R_s. Consider sensors S_0 and S_1 at positions (x_0, y_0) and (x_1, y_1), respectively, illustrated in Fig. 2. Each sensor is responsible for only forwarding the target estimated position $(x_\mathrm{t}, y_\mathrm{t})$ if the position lies on the side of its centre and the line AB which bisects the lens.

From Fig. 2, if S_0 estimates the target position at point $T(x_\mathrm{t}, y_\mathrm{t})$, it will forward data to the sink, since the target position is between its center and the line AB, however, if S_1 estimates the target position at point $T(x_\mathrm{t}, y_\mathrm{t})$, it will not forward data to the sink, since the target position is beyond the line AB.

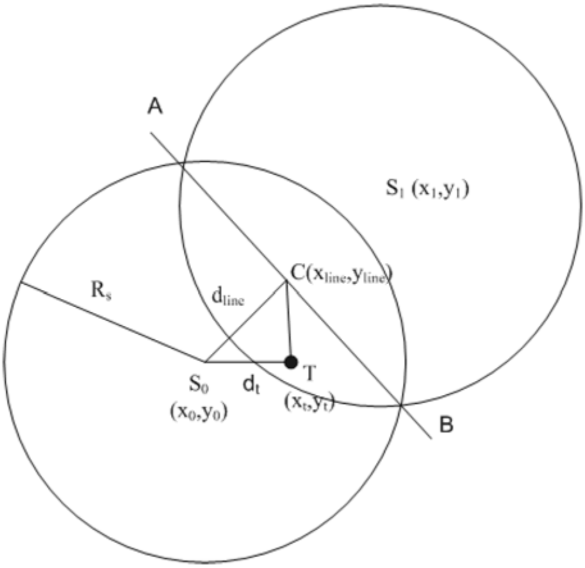


Fig. 2 Sensors with overlapping sensing areas

The coordinates of points A and B are determined by simple geometric calculations; see (6) to (12) and we use these points to determine the equation of the line joining A and B and bisecting the lens. If r_0 and r_1 are the radii of the two sensors ($r_0 = r_1 = R_s$), (x_0, y_0) are the coordinates of S_0, (x_1, y_1) are the coordinates of S_1, d is the distance between the centers of S_0 and S_1 and (x, y) are the coordinates of the intersection points, we have

$$d = \sqrt{((x_0 - x_1)^2 + (y_0 - y_1)^2)}, \tag{6}$$

$$K = \frac{1}{4}\sqrt{(((r_0 + r_1)^2 - d^2)(d^2 - (r_0 - r_1)^2))}, \tag{7}$$

$$x = \frac{(x_1 + x_0)}{2} + \left(\frac{(x_1 - x_0)(r_0^2 - r_1^2)}{2d^2}\right) \pm \left(\frac{2K(y_1 - y_0)}{d^2}\right), \tag{8}$$

$$y = \frac{(y_1 + y_0)}{2} + \left(\frac{(y_1 - y_0)(r_0^2 - r_1^2)}{2d^2}\right) \pm \left(\frac{(-2K)(x_1 - x_0)}{d^2}\right). \tag{9}$$

Substituting $r_0 = r_1 = R_s$ in (7), (8), and (9) we have

$$K = \frac{d}{4}\sqrt{4R_s^2 - d^2}, \tag{10}$$

$$x = \frac{(x_1 + x_0)}{2} \pm \frac{2K(y_1 - y_0)}{d^2}, \tag{11}$$

$$y = \frac{(y_1 + y_0)}{2} \pm \frac{(-2K)(x_1 - x_0)}{d^2}. \tag{12}$$

The equation of the line AB is given by (13).

$$y = mx + (y_{\mathrm{A}} - (mx_{\mathrm{A}})), \tag{13}$$

where $(x_{\mathrm{A}}, y_{\mathrm{A}})$ are the coordinates of A, and $(x_{\mathrm{B}}, y_{\mathrm{B}})$ are the coordinates of B and

$$m = \frac{(y_{\mathrm{A}} - y_{\mathrm{B}})}{(x_{\mathrm{A}} - x_{\mathrm{B}})}. \tag{14}$$

The coordinates of point $C(x_{\mathrm{line}} = x_{\mathrm{t}}, y_{\mathrm{line}})$ are obtained by substituting $x = x_{\mathrm{t}}$ in (13). We can then calculate the distances d_{line} and d_{t} from S_0, where d_{line} is the distance from the sensor S_0 to the line AB and d_{t} is the distance from sensor S_0 to the target estimated position.

If $d_{\mathrm{t}} <= d_{\mathrm{line}}$, then the data is not redundant and S_0 is allowed to send the data. If $d_{\mathrm{t}} > d_{\mathrm{line}}$, then the data is redundant, and S_1 is responsible for sending the data.

4 Simulation studies

We analyze the performance of our algorithms via simulations using NS2. We use two performance metrics: network lifetime and tracking accuracy and compared our results against a baseline. The baseline was formed by simulating a tracking scenario where any sensor in the cluster that could receive a signal from the target sends its data to the cluster head. We use 52 nodes divided into four clusters and each sensor begins with an initial energy of 3 J. The transmission and reception energy is 0.175 J, idle energy is 0.035 J, and the sensing energy is 1.75 μJ. The nodes have a sensing range of 50 m, communication range of 100 m, and the sensing area is 300 m × 300 m. Also, unless otherwise stated, we used $\alpha_m(2, 1)$ and $W_U = 0.2$. The target follows a random waypoint model with very short pause time and generally starts at the edge of the sensor field and moves inward with random motion through all the clusters. The results given are the averaged results over ten similar scenarios.

4.1 Network lifetime

Figure 3 shows the effect of varying the weight threshold W_U, on the network lifetime when using only the RARE-Area algorithm. As W_U increases from 0.2 to 0.5, there is a corresponding increase in the network lifetime. Application of the RARE-Area algorithm limits the nodes participating in tracking to only those with the required quality of data. As the weight threshold increases, higher and higher quality data is required and fewer sensors are able to meet this requirement. This means that compared to the base case, fewer and fewer nodes are being used to track the object as W_U increases so energy is saved.

We also see that with $W_U = 0.2$ and application of the RARE-Area algorithm only, the energy saved is not significant. The weight threshold W_U specifies the minimum required quality of data for tracking and if the value of W_U is too low, e.g., $W = 0.2$, and we only use the RARE-Area algorithm, then all sensors are able to meet the quality requirement and the energy used is the same as in the base case.

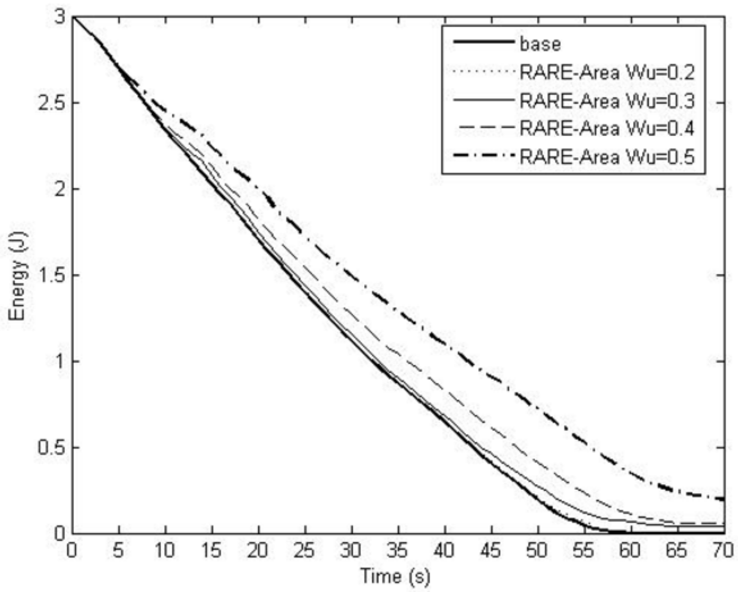


Fig. 3 Effect of varying W_U on network lifetime using RARE-Area only

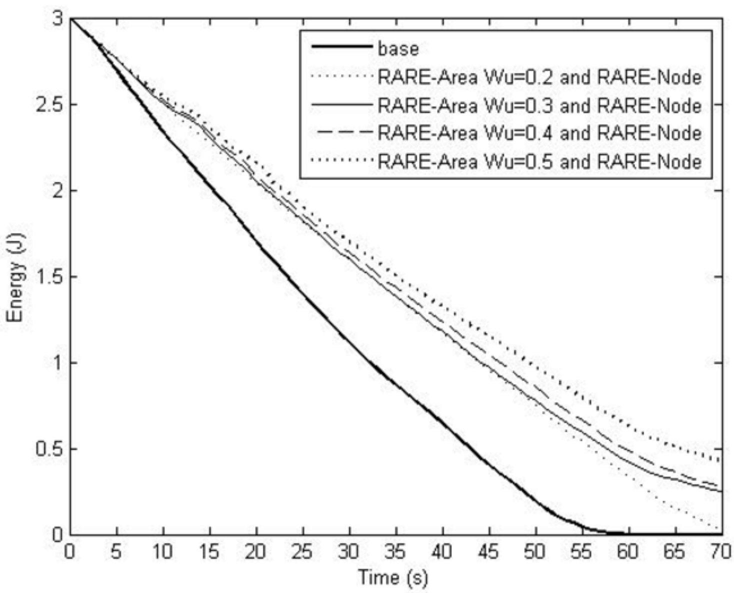


Fig. 4 Effect of varying W_U on network lifetime using both RARE-Area and RARE-Node

Figure 4 shows the effect of using both algorithms and a similar trend to Fig. 3 is observed, but with a larger increase in network lifetime for each case when compared to the corresponding case in Fig. 3. When we apply the RARE-Node algorithm, we reduce the amount of redundant data to be sent by the sensors to the cluster head. This energy saved by reducing communication adds to that already saved by using the RARE-Area algorithm.

As we increase W_U, the amount of increase in the lifetime we see between using RARE-Area only and using both algorithms generally decreases. As W_U increases, fewer and fewer sensors are able to meet the quality requirement. When we add the RARE-Node algorithms, we still obtain savings, but because we have fewer sensors carrying out the redundancy check, there is less redundant data and the overall effect of the energy saved is smaller.

4.2 Tracking accuracy

Figures 5 and 6 illustrate the difference in the tracking accuracy when we apply our algorithms with different weights. Generally, as W_U increases, the average tracking error increases. At the cluster heads, the transmitted target position at a particular time is the averaged result of the estimated position received from the sensors for that period. When using the RARE-Area algorithm, as we increase W_U we require higher quality data and this limits the sensors that can provide it. As fewer sensors are able to send data, the averaged result is more prone to errors because although we have received less data and it is high quality data, the data is not necessarily accurate due to errors in the trilateration method and errors obtained from the received signal strength. So, we observe an increase in the tracking error.

We also note from the graphs that application of only the RARE-Area algorithm results in a larger increase in the error as compared to that obtained when we use both the RARE-Area algorithm and the RARE-Node algorithm. Application of the RARE-Node algorithm reduces the redundant data and so when averaging at the cluster head, the errors are smoothed out. With $W_U = 0.2$ to 0.3, there is generally no significant difference in the tracking error when we use both RARE-Area and RARE-Node algorithms. With $W_U = 0.4$ to 0.5, the change in the tracking accuracy is more noticeable especially if we are only using the RARE-Area algorithm. This implies that with a low to medium weighting threshold our algorithm can be used for tracking targets in a sensor network and our approach provides significant energy savings.

4.3 Effect of varying motion factor

The motion factor $\alpha_m(m, s)$ was varied in order to determine its effect on our algorithms. We used three values: $\alpha_m(1, 1)$ where the motion status of the target was ignored, i.e., weighed equally; $\alpha_m(2, 1)$ where the weighting ratio of when the target is moving to when it is stationary is 2:1, i.e., small difference in weighting; $\alpha_m(5, 1)$ where the weighting ratio of when the target is moving to when it is stationary is 5:1, i.e., large difference in weighting. We ran simulations with $W_U = 0.2$ and 0.4.

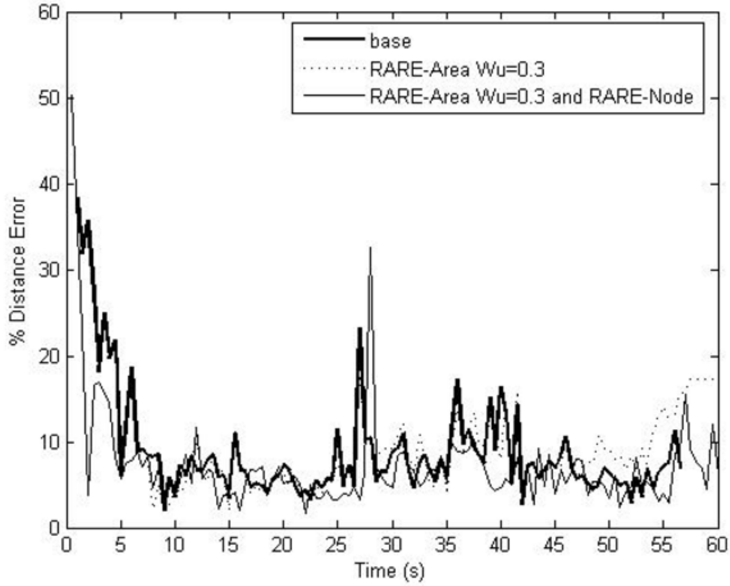


Fig. 5 Effect of RARE algorithms on tracking accuracy with $W_U = 0.3$

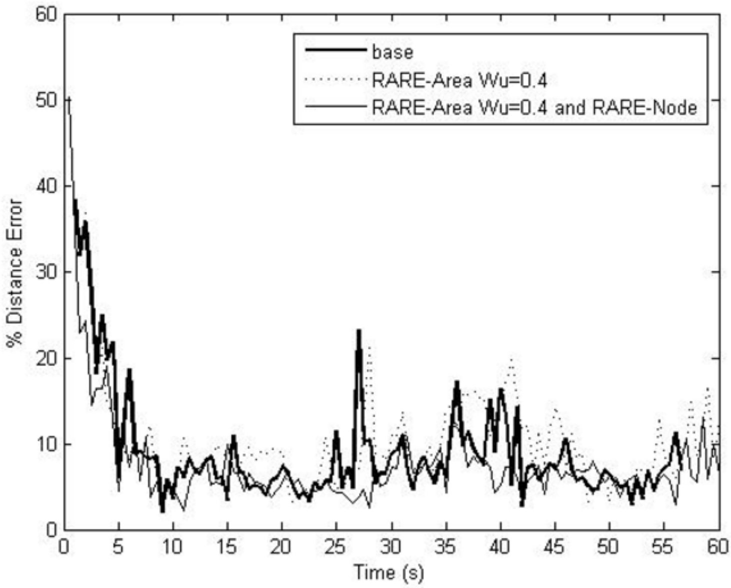


Fig. 6 Effect of RARE algorithms on tracking accuracy with $W_U = 0.4$

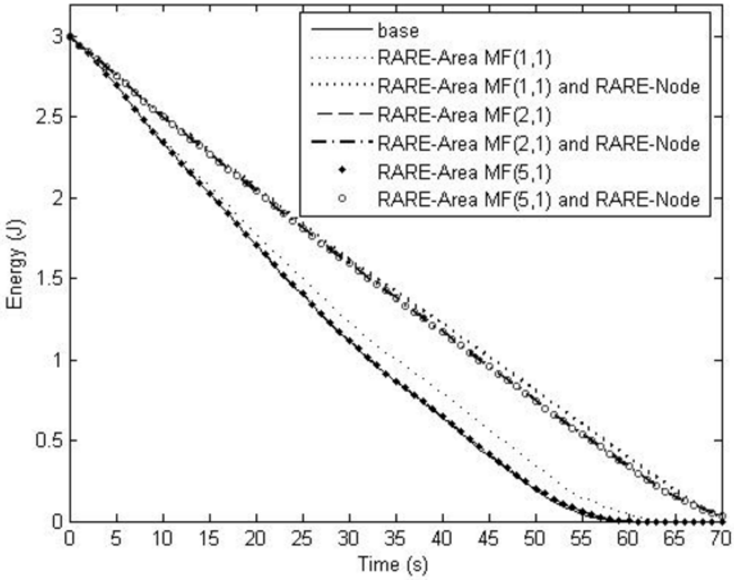


Fig. 7 Effect of varying $\alpha_m(m, s)$ on network lifetime with $W_U = 0.2$

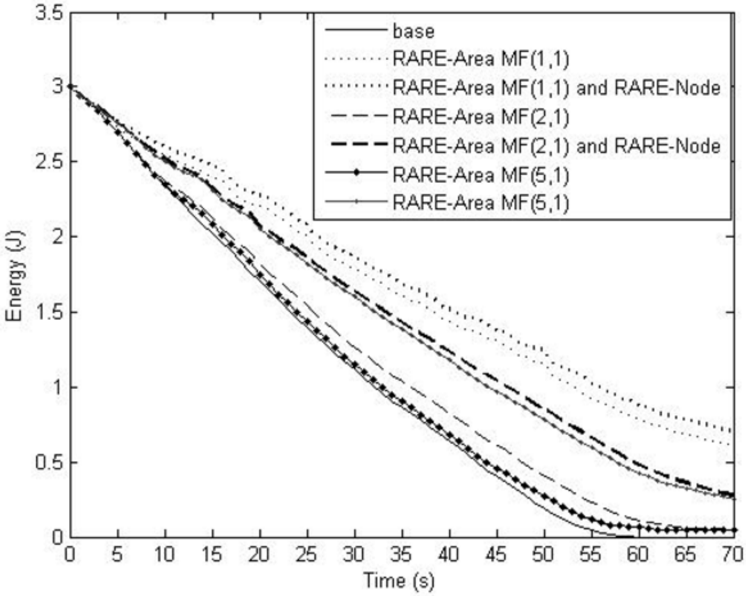


Fig. 8 Effect of varying $\alpha_m(m, s)$ on network lifetime with $W_U = 0.4$

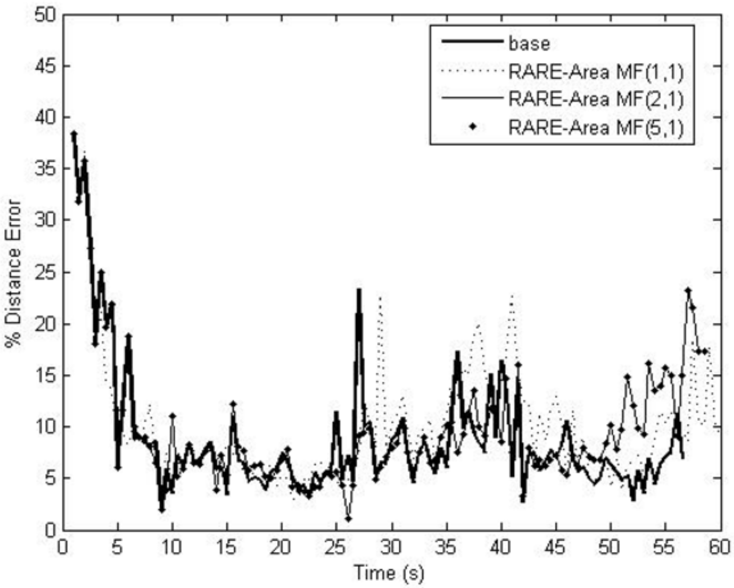


Fig. 9 Effect of varying $\alpha_m(m, s)$ on accuracy using RARE-Area only and $W_U = 0.2$

Network lifetime. Figures 7 and 8 show the effect on network lifetime when we vary the motion factor at different values of W_U. The largest increase in network lifetime is seen with $\alpha_m(1, 1)$.

As the motion factor ratio increases, we see a smaller increase in network lifetime indicating that when we differentiate between a moving and a stationary target, we have less energy savings than when we ignore the motion status. This is caused by the target motion characteristics. For our target motion, the time that the target spends stationary is small when compared to the time the target is in motion so we have a lot of data for when the target is moving and little for when the target is stationary.

If the motion factor ratio is high, then the weighting given to the data when the target is moving is high and if the weight threshold is low (for example at $W_U = 0.2$), then many sensors can provide the data thus not a lot of energy is saved. When we ignore the motion status, i.e., the ratio for a moving and stationary target is the same, the weighting given to the data is not as high and fewer sensors can provide the required quality thus energy is saved. From this, we also see that the energy saving effect of the motion factor ratio also depends on the set weight threshold W_U. With a low weight threshold and a high motion factor ratio, we get less energy savings because many sensors can provide the low quality data required, and hence a lot of energy is used. To increase energy efficiency, a higher weighting should be implemented with a high motion factor ratio.

Tracking accuracy. From Figs. 9, 10, 11, 12 generally, we see that the tracking accuracy is better with application of both algorithms. We also note that as the motion factor increases, the effect on the tracking error reduces. This is observed more clearly from Figs. 11 and 12 where we have a higher weight threshold. The increase

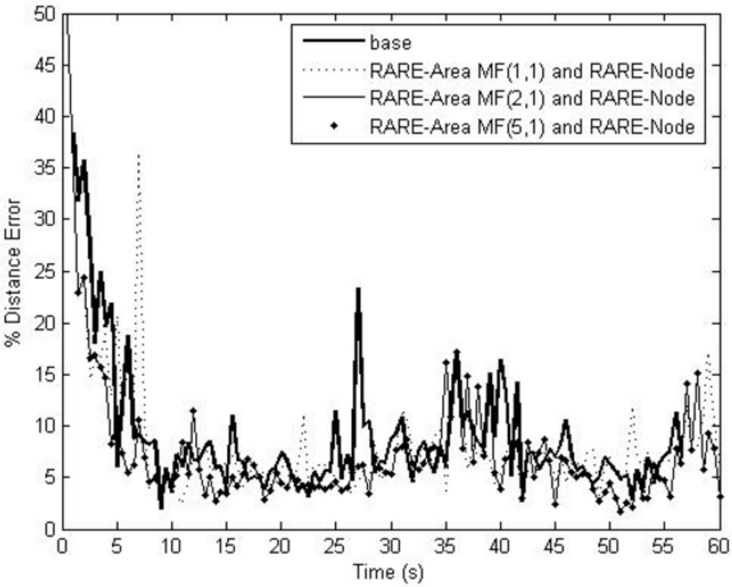


Fig. 10 Effect of varying $\alpha_m(m, s)$ on accuracy using RARE-Area and RARE-Node and $W_U = 0.2$

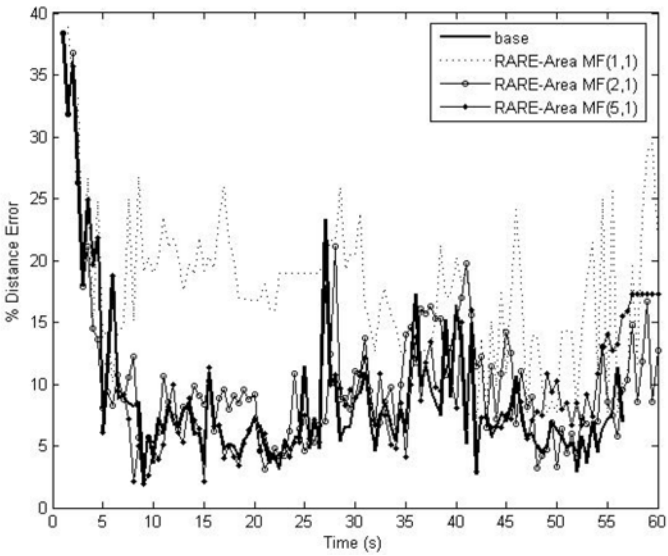


Fig. 11 Effect of varying $\alpha_m(m, s)$ on accuracy using RARE-Area only and $W_U = 0.4$

in accuracy is because as the motion factor ratio increases, more data is sent to the cluster head and so the result of the fusion process is more accurate. From our results when varying the motion factor, we can conclude that if the target motion characteristics contain a lot of pauses, i.e., the time that the target spends when it is stationary

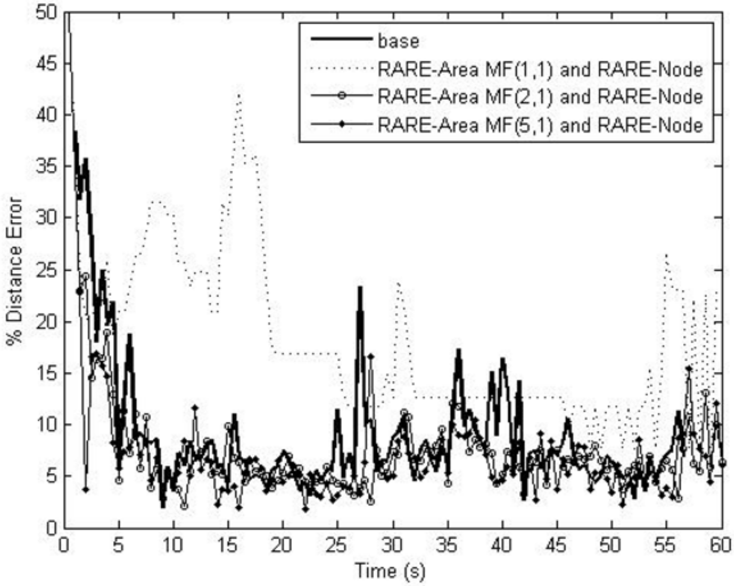


Fig. 12 Effect of varying $\alpha_m(m, s)$ on accuracy using RARE-Area and RARE-Node and $W_U = 0.4$

is high, then more energy savings can be obtained with a higher motion factor ratio. If the time the target spends stationary is low when compared with the time it spends in motion, then more energy savings are obtained by having a low motion factor ratio or by giving equal weight to the data when the target is moving or stationary.

5 Conclusion and future work

For target tracking in wireless sensor networks, energy conservation plays an important role and we proposed an energy-efficient target tracking protocol that utilizes two algorithms. The RARE-Area algorithm determines which sensors will participate in tracking by monitoring the data quality and the RARE-Node algorithm determines which data is sent to the cluster head. Simulation studies showed that with low to medium values of weight threshold W_U and implementation of both algorithms provides significant energy savings while not having too much of a negative effect on tracking accuracy.

Future research includes comparing the performance of the RARE algorithms with other target tracking protocols and investigation into the feasibility of dynamic adjustment of the various settings, e.g., weight threshold and motion factor ratio in order to improve performance.

Acknowledgements This work is supported by the Hunan Provincial Natural Science Foundation of China for Distinguished Young Scholars under Grant No. 07JJ1010, the National Natural Science Foundation of China under Grant Nos. 90718034 and 60533040, 60811130528, 60725208, the National High-Tech Research and Development Plan of China (863 Plan) under Grant Nos. 2008AA01Z106 and 2006AA01Z202, Shanghai Pujiang Plan No. 07pj14049, and the Program for Changjiang Scholars and the Innovative Research Team in University under Grant Number IRT0661.

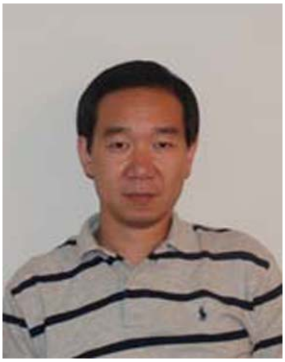
References

1. Kuorilehto M, Hannikainen M, Hamalainen TD (2005) A survey of application distribution in wireless sensor networks. EURASIP J Wirel Commun Netw 5:774–788
2. Sinha, Chandrakasan A (2001) Energy efficient system partitioning for distributed wireless sensor networks. In: Proc of IEEE intl conf on acoustics, speech and signal processing, vol 2, pp 905–908
3. Kompella RR, Snoeren AC (2003) Practical lazy scheduling in wireless sensor networks. In: Proc of the 1st intl conf on embedded networked sensor systems, SenSys'03, Los Angeles, pp 280–291
4. Wang G, Cao J, Wang H, Guo M (2007) Polynomial regression for data gathering in environmental monitoring applications. In: Proc of the 2007 IEEE global telecom conf (GLOBECOM 2007), Nov 2007, Washington DC, USA, pp 1307–1311
5. Goel S, Imielinski T (2001) Prediction-based monitoring in sensor networks: taking lessons from MPEG. ACM SIGCOMM Comput Commun Rev 31(5):82–98
6. Wang G, Wang H, Cao J, Guo M (2007) Energy efficient dual prediction based data fathering for environmental monitoring applications. In: Proc of the 2007 IEEE wireless communications and networking conf (WCNC 2007), Hong Kong, March 2007, pp 3516–3521
7. Wang G, Wang T, Jia W, Guo M, Li J (2009) Adaptive location updates for mobile sinks in wireless sensor networks. J Supercomput 47(2):127–145
8. Olule E, Wang G, Guo M, Dong M (2007) RARE: an energy efficient target tracking protocol for wireless sensor networks. In: Intl conf on parallel processing workshops (ICPP 2007), Xi'an, China, Sept 2007, pp 76–82
9. Yang H, Sikdar B (2003) A protocol for tracking mobile targets using sensor networks. In: Proc of the first IEEE intl workshop on sensor network protocols and applications, May 2003, pp 71–81
10. He and G, Hou JC (2005) Tracking targets with quality in wireless sensor networks. In: Proc of the 13th IEEE intl conf. on network protocols (ICNP 2005), 2005, pp 63–74
11. Zhao F, Shin J, Reich J (2002) Information-driven dynamic sensor collaboration for tracking applications. IEEE Signal Process Mag 19(2):61–72
12. Chu M, Haussecker H, Zhao F (2002) Scalable information driven sensor querying and routing for ad hoc heterogeneous sensor networks. Intl J High Perform Comput Appl 16(3):90–110
13. Gao V, Wu K, Li F (2003) Analysis on the redundancy of wireless sensor networks. In: Proc of 2nd ACM intl workshop on wireless sensor networks and applications (WSNA 2003), San Diego, California, Sept 2003, pp 108–114
14. Niculescu D, Nath B (2001) Ad hoc positioning system (APS). In: Proc of the 2001 IEEE global telecommunications conf (GLOBECOM 2001), 2001, vol 5, San Antonio, pp 2926–2931
15. Rappaport TS (2001) Wireless communications: principles and practices, 2nd edn. Prentice Hall, New York

Minyi Guo received his Ph.D. degree in Computer Science from the University of Tsukuba, Japan. Before 2000, Dr. Guo had been a research scientist of NEC Corp., Japan. He is now a distinguished chair professor at the Department of Computer Science and Engineering, Shanghai Jiao Tong University, China, and a professor of the School of Information Engineering, Dalian Maritime University. He was also a visiting professor of Georgia State University, USA, Hong Kong Polytechnic University, University of Hong Kong, National Sun Yet-Sen University in Taiwan, University of Waterloo, Canada and University of New South Wales, Australia. He is also a professor of the University of Aizu, Japan. Dr. Guo has published more than 150 research papers in international journals and conferences. Dr. Guo has served as general chair, program committee, or organizing committee chair for many international conferences. He is the founder of International Conference on Parallel and Distributed Processing and Applications (ISPA), and International Conference on Embedded and Ubiquitous Computing (EUC). He is the editor-in-chief of the Journal of Embedded Systems. He is also on the editorial board of Journal of Pervasive Computing and Communications, International Journal of High Performance Computing and Networking, Journal of Embedded Computing, Journal of Parallel and Distributed Scientific and Engineering Computing, and International Journal of Computer and Applications. Dr. Guo's research interests include parallel and distributed processing, parallelizing compilers, pervasive computing, embedded software optimization, molecular computing, and software engineering. He is a senior member of IEEE, a member of the ACM, IPSJ, and IEICE.

Elizabeth Olule received her B.Sc. degree in Electrical Engineering in 2001 from Makerere University, Uganda, and her M.Sc. degree in Computer Applications Technology from Central South University, China, in 2008. She is currently working as a VAS Engineer Planning Engineer with MTN Uganda.

Guojun Wang received his B.Sc. degree in Geophysics, M.Sc. degree in Computer Science, and Ph.D. degree in Computer Science, from the Central South University, in 1992, 1996, 2002, respectively. He is currently a Professor at Central South University, China. He is the Director of the Trusted Computing Institute, formerly the Mobile Computing Institute, in the University. He is also a Vice Head of the Department of Computer Science and Technology in the University. He was a Research Fellow in the Hong Kong Polytechnic University, Hong Kong, from 2003–2005, a Visiting Researcher in the University of Aizu, Japan, from 2006–2007, and a Visiting Scholar in Florida Atlantic University, US, from 2009–2010. His research interests include trusted computing, mobile computing, pervasive computing, and software engineering. He has published more than 140 technical papers and books/chapters in the above areas. He is an associate editor or on the editorial board of some international journals including Security and Communication Networks, Journal of Security and Telecommunications, Journal of Computer Systems, Networking, and Communications, and International Journal of Multimedia and Ubiquitous Engineering. He has also served as guest editor-in-chief or guest editor for some international journals including IEICE Transactions on Information and Systems, Wiley Security and Communication Networks, and Journal of Computers (Academy Publisher). He has also served as a general chair, program chair, program vice-chair, track chair, publication chair, publicity chair, and program committee member for more than 90 international conferences and workshops such as GLOBECOM, ICC, WCNC, AINA, HPCC, IWCMC, EUC, ISPA, ICYCS, CSA, ATC, TrustCom and TSP. He is a senior member of the China Computer Federation, the Academic Committee member of the YOCSEF of the China Computer Federation, the chair of the YOCSEF Changsha of the China Computer Federation (2007–2008), and a member of several Technical Committees of China Computer Federation, including Fault Tolerant Computing, Pervasive Computing, Software Engineering and E-Government, and Office Automation.



Song Guo received the Ph.D. degree in Computer Science from the University of Ottawa, Canada in 2005. He then held a position with the University of British Columbia on an NSERC (Natural Sciences and Engineering Research Council of Canada) postdoctoral fellowship. From 2006 to 2007, he was Assistant Professor at the University of Northern British Columbia, Canada. He is currently Assistant Professor at School of Computer Science and Engineering, the University of Aizu, Japan. His research interests are in the areas of protocol design and performance analysis for communication networks, with a special emphasis on wireless ad hoc and sensor networks for reliable, energy-efficient, and cost-effective communications.