Energy-Efficient Target Localization Based on a Prediction Model*

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Abstract. In this paper, we propose an energy-efficient target localization scheme (TLS) based on a prediction model that can reveal the most likely zone the target will be in, and also a corresponding two-step communication protocol between base station (BS) and sensors. BS uses a query mechanism to determine which sensors should be used for detailed information according to a limited amount of data received from the sensors. This scheme reduces both energy consumption and communication bandwidth requirement, prolongs the lifetime of the wireless sensor networks. Simulation results indicate that it can achieve a high accuracy while saving a large amount of energy.

Keywords: wireless sensor networks, energy-efficient, prediction model, TLS.

1 Introduction

Many sensor networks need to handle physical entities that move in the environment (e.g. habitat monitoring [1] and intruder tracking [2]). Only sensors close to the target should participate in the aggregation of data associated with that target, since activating distant sensor nodes wastes precious energy without improving sensing fidelity. In recent research, a reliable multicast method has been proposed to solve this kind of problem in literature [3] and achieved comparatively good results. Since energy management in the localization event is crucial for battery-driven sensor nodes where are severely energy constrained, here we focus on reducing energy consumption in wireless sensor networks for target localization.

In general, a sensor network has an almost constant rate of energy consumption if no target activities are detected in the sensor field. The minimization of energy consumption for an active sensor network with target activities is more complicated since target detection involves collaborative sensing and communication with different sensors.

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Though many literatures [4] [7] [8] [9] [11] have already introduced different methods to save energy during tracking procedure, without prediction knowledge of the target, most of energy consumed in the localization event still has been wasted in keeping too many sensors in the sensing state while actually only a few sensors will be enough.

To continuously monitor a mobile entity, a sensor network must maintain an active group that moves at the same velocity as the entity. This energy-efficient operation requires a prediction model to make conjectures about future target positions. Here in this paper, an energy-efficient target localization scheme (TLS) based on a prediction model has been posted. Since estimating the accurate future positions is almost impossible, the prediction model uses previous target position information to reveal the most likely zone (We call this zone as an awaken zone (AZ)) target will be in at the next moment, and then BS sends commands to wake up enough sensors inside AZ to track the target. We will show how to calculate AZ at time i and prove that there will always be some sensors in AZ that can detect the target under some assumptions. To the maximum of my knowledge, no previous work has been done on the exact prediction model of saving energy.

Two distinct improving results have been obtained:

- This scheme reduces averagely 80% energy consumption during the track procedure as the simulation shows.
- Analysis on TLS indicates that the requirement of communication bandwidth can also be reduced since the packets generated in the communication protocol are all kept very small.

In the past few years, a number of detecting and tracking methods have been proposed [4] [5] [6] [7] [8] [9] [10] [11] [12]. Those literatures focus either on how to reduce energy consumption or on how to localize a target more accurately.

Yi Zou and Krishnendu Chakrabarty have proposed an energy-aware target detection and localization strategy for cluster-based wireless networks in [4]. This strategy is based on a posteriori algorithm with a two-step communication protocol between cluster head and the sensor within the cluster. It uses a detection probability table which contains entries for all possible detection reports from those sensors that can detect a target at grid points to find out the target's max-probability position. In [7], T.Clouqueur and his copartners have discussed sensor deployment for collaborative target detection where path exposure is used as a measure of the effectiveness of the sensor deployment. Richard R. Brooks and his copartner have proposed a formulation which is anchored on location-aware data routing to conserve system resources, such as energy and bandwidth [9]. Literature [12] models the problem of a sensor network tracking a moving target as a Markov model of mobility, that is, the position of the target at time i depends only on its position at time $i-1$.

Range-based protocols use absolute point-to-point distance or angle information to calculate location between neighboring sensors. Common techniques for distance/angle estimation include Time of Arrival (TOA) [14], Time Difference of Arrival (TDOA) [13], Angle of Arrival (AOA) [15], and Received Signal Strength (RSS) [13]. Those protocols all can work well in our scheme.

Considering that sensor density inside some AZ may be too high, we only need to wake up enough sensors in AZ instead of all sensors. Here we use the ASCENT method proposed in [16].

The reminder of the paper is organized as follows. Section 2 introduces system model and a few consumptions. Section 3 describes details about TLS. Section 4 shows energy consumption analysis. In section 5, we present simulation results and our practical considerations. Section 6 concludes the paper and outlines directions for future work.

2 System Model and Assumptions

In this section, we will introduce several assumptions in part A. In part B, a prediction model is described, and an exact definition of AZ is given with the existence of sensors inside that will detect the target in the future moment proven.

A. Assumptions

For a simple analysis, we make the following assumptions in this paper:

- All sensors remain stationary after deployment phase.
- Sensors are able to communicate with BS, while BS has the exact deployment information.
- BS is much more powerful in computation capability than sensors. BS is responsible for all calculation, while sensors are functioning mainly as data collecting devices.
- Considering a wireless sensor network with N sensors deployed averagely in dual space, we regard it reasonable to assume that there are k sensors per πr_s^2 ($k \geq 1, k \in Z^+$), (r_s represents the detection range of sensors).

B. Prediction Model

In this part, we introduce the prediction model for target localization. A key contribution of this model is that it supplies BS with the information of an area where the target will be at the next moment. If the speed of a target moving in a wireless sensor network is lower than a threshold (We will show that the threshold in actual applications can be set high enough in Section 6), we can prove that there is at least one sensor inside that area which can detect the target.

To predict the target's position at time i , we should use the previous position information for target trace is always continuous in an actual environment.

Definition 1. $\bar{I}$, $\bar{I}$ is the target trace. $\bar{I} = (I_0(x_0, y_0), \dots, I_i(x_i, y_i), \dots)$, $I_i(x_i, y_i)$ $i \geq 0$ represents the target's position at time i .

Given the target trace from time 0 to time $i-1$: $\bar{I} = (I_0(x_0, y_0), \dots, I_{i-1}(x_{i-1}, y_{i-1}))$, we model target's position at time i ($i \geq 1$) following a two-dimensional Gaussian distribution, which is centered at the prediction point (x_{pre-i}, y_{pre-i}) . Namely, the

mean of the Gaussian distribution μ equals (x_{pre-i}, y_{pre-i}) , and the probability distribution function (PDF) for the target's position at time i is the following:

$$f(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x-x_{pre-i})^2 + (y-y_{pre-i})^2}{2\sigma^2}} \quad (1)$$

(Here σ is the standard deviation). Without loss of generality, we assume that the standard deviation for all PDF is identical.

The prediction point (x_{pre-i}, y_{pre-i}) represents the most possible position of the target at time i . It depends on the prior information of the target trace. Here we apply two different methods according to different situations in the practical applications.

I. Suppose the target walks along the line: $y = y_{i-1} + (x - x_{i-1}) \tan \theta$, then we can define the prediction point as: (Δt is the time interval between time $i-1$ and i)

$$\begin{cases} x_{pre-i} = x_{i-1} + V_{i-1} \Delta t \cos \theta \\ y_{pre-i} = y_{i-1} + V_{i-1} \Delta t \sin \theta \end{cases} \quad (i \geq 2 \quad \theta = \arctan(\frac{y_{i-1} - y_{i-2}}{x_{i-1} - x_{i-2}})) \quad (2)$$

V_{i-1} represents target's instantaneous speed at time $i-1$:

$$V_{i-1} = \frac{|I_{i-1} - I_{i-2}|}{\Delta t} \quad i \geq 2 \quad (3)$$

II. If we do not have much useful prior information of the target, which is common in actual environment, then the target position at time $i-1$ would be used as the prediction point:

$$\begin{cases} x_{pre-i} = x_{i-1} \\ y_{pre-i} = y_{i-1} \end{cases} \quad i \geq 1 \quad (4)$$

Since it is difficult to estimate future target position accurately, here instead of predicting the target position at time i , we will predict an area large enough in which the target will be by using (1).

According to (1), if the target trace $\vec{I} = (I_0(x_0, y_0), \dots, I_{i-1}(x_{i-1}, y_{i-1}))$ is known, the probability that target will be in the round centered at prediction point (x_{pre-i}, y_{pre-i}) with radius R that we can calculate using Theorem1 (introduced below) is greater than a given threshold $H (0 \leq H \leq 1)$. It means that we can calculate an area in which the target will be at time i with a probability greater than H .

Theorem 1. Given a threshold $H (0 \leq H \leq 1)$, $\exists R \geq \sigma \sqrt{2 \ln \frac{1}{1-H}}$, the probability that target will be in the round centered at prediction point (x_{pre-i}, y_{pre-i}) with radius R at time i is larger than H .

Proof: See Appendix A. □

We have mentioned before that BS would wake up enough sensors in an awaken zone (AZ) for future position detection, and an exact definition of AZ is given below:

Definition 2. (Awaken Zone-i) Awaken Zone-i is a round centered at point (x_{pre-i}, y_{pre-i}) with radius $R = \sigma \sqrt{2 \ln \frac{1}{1-H}}$. BS sends command to wake up enough sensors inside AS-i to keep sensing target. (We will use AZ instead of AZ-i in the following context)

Although the threshold H cannot be preset in the paper, we still suggest that in practical applications H should be larger than 90% to make sure enough sensors in AZ can detect the target.

In the following part, we will approve the existence of at least one sensor in AZ we defined could detect the target at time i .

Definition 3. V_H . V_H is the maximum speed a target can have if it can be detected by sensors in AZ. $V_H = \frac{l_{\max}}{\Delta t}$, where $l_{\max}$ is the result of equations following: (r_s represents the detection range of sensors):

$$\begin{cases} S = r_s^2 \theta_1 - r_s^2 \sin \theta_1 \cos \theta_1 + R^2 \theta_2 - R^2 \sin \theta_2 \cos \theta_2 \\ R = \sigma \sqrt{2 \ln \frac{1}{1-H}} \\ S * k / \pi r_s^2 = 1 \end{cases}$$

$$\theta_1 = \cos^{-1} \left(\frac{r_s^2 + l_{\max}^2 - R^2}{2 r_s l_{\max}} \right) \quad \theta_2 = \cos^{-1} \left(\frac{R^2 + l_{\max}^2 - r_s^2}{2 R l_{\max}} \right)$$

Theorem 2. According to our pervious assumption: there are k sensors per πr_s^2 averagely. ($k \geq 1, k \in \mathbb{Z}^+$), if $V_i \leq V_H$, there will be at least one sensor inside Awakening Zone-i that can detect the target at time i .

Proof: See Appendix A □

In this section, we have introduced our sensor nodes mode, prediction model and an exact definition of AZ has been given including how to calculate an AZ-i. We have also proven that the existence of at least one sensor inside the AZ-i can detect the target at time i under some assumptions which will be discussed in Section 6.

3 Target Localization Scheme (TLS)

First we will discuss the common flow about TLS in this section, and then we will show detailed information about data types used in the communication protocol in part A. Since we apply distributed algorithms in TLS, two different types of timer shown in

part B are needed in the protocol. To save precious energy, after gathering draw date from sensors that have detected the target at current time, TLS uses a query mechanism to determine which sensors should be queried for further information which will be described in part C.

A. Data Types

There are four different data types in our communication protocol.

AWK: when a sensor node in idle state receives an AWK packet, it wakes up, sets up a KEEPALIVE timer and keeps sensing for a constant time Δt . If it is already in sensing state, then the KEEPALIVE timer would be reset. An AWK packet is very small; actually, one bit will be enough.

RPT: when a sensor node detects an object, it generates a RPT packet indicating rest energy it has and the distance between them then sends it to BS.

QUY: BS sends a QUY packet to a sensor node, and waits for a DAT packet. A query message can also be encoded into a few bits.

DAT: When a sensor node receives a QUY packet, it sends a DAT packet to BS. A DAT packet includes detailed information about the target.

Since all the packets generated in our communication protocol are very small, in fact all the information can be encoded into only a few bits, TLS could reduce bandwidth requirement and the latency as well.

B. KEEPALIVE Timer and WAIT Timer

When a sensor in the idle state receives an AWK packet, it wakes up and set a KEEPALIVE timer. While the KEEPALIVE timer does not expire, it keeps sensing. But if a sensor already in the sensing state receives an AWK packet, it would reset the timer and keep sensing.

After BS receives a RPT message for time i , it sets a WAIT timer which indicates how long BS should wait for all RPT messages. When WAIT timer expires, BS executes Query Mechanism to query sensors for detailed information. We can set $\frac{3\Delta t}{4}$ as its value.

C. BS Query Mechanism

To save energy, we only need to query $k_q(i)$ sensors for detailed information at time i .

When BS receives a REQ packet, if it is the first time to receive a detection report for time i , BS sets a WAIT timer. After the WAIT timer expires, BS considers that all sensor nodes that detect the target at time slot Δt between time $i-1$ and time i have been reported. Then it uses Query Mechanism to select sensors to query.

Suppose there are $k(i)$ ($k(i) \geq k_q(i)$) sensors which have sent $RPT < d, E_r >$ packets to BS at time i , (d represents the distance between the sensor and the target, E_r represents rest energy of the sensor, r_s represents the sensing range). We build the following equation:

$$F = \alpha \frac{E_r}{E} + (1 - \alpha) \frac{d}{r_s} \quad 0 \leq \alpha \leq 1 \quad (5)$$

BS must query sensor nodes that have larger F for further detailed information. Obviously, to save precious energy, we must query the sensor nodes which have the most rest energy. But if we want to achieve a higher accuracy, we should query the sensor nodes which have a nearer distance to the target. So we build this equation considering both the energy and accuracy to decide which sensors to query.

In this section, we have described detailed information about our scheme, and in Section 5, we will discuss the advantages of TLS in energy consumption.

4 Energy Consumption Analysis

In this section, to show TLS's impact on energy consumption, we will compare energy consumption between two different tracking schemes: Tracking an object in WSN without TLS and with TLS. A simplified sensor energy consumption model is used here as a metric for evaluating energy consumption. Suppose a sensor has three basic energy consumption types: sensing, active, idle, and these power values are $\varphi_s, \varphi_a, \varphi_i$.

Definition 4. T_r , if some sensor node detects the target, it needs to send a RPT packet $\langle d, E_r \rangle$ to BS, T_r represents the time needed to transfer this peculiar packet. Since usually the length of this packet is constant, we assume that T_r is a constant value.

Definition 5. T_s , if some sensor node has received a QUY packet from BS, it needs to send BS a DAT packet. We define T_s as the time the sensor used to receive this QUY packet plus the time it needs to transfer a DAT packet to BS. It is also reasonable to assume T_s as a constant value.

A. Energy Consumption Analysis for Tracking an Object in WSN Without TLS

Without available prediction information, we must keep all sensor nodes in sensing state to make sure the target can be detected. Assume there are $k(i)$ sensors that can detect the target at time i , but only $k_q(i) (k_q(i) \leq k(i))$ sensors would be queried by BS for detailed information.

In time slot Δt between time $i-1$ and i :

Number of sensors in sensing state: N

Number of sensors that need to generate RPT packets: $k(i)$

Number of sensors that need to generate DAT packets: $k_q(i)$

We evaluate the energy consumption as following:

$$E_i = N\varphi_s\Delta t + k_q(i)\varphi_aT_s + k(i)\varphi_aT_r \quad (6)$$

$$E = \sum_{i=0}^{t_{end}} E_i \quad (7)$$

B. Energy Consumption Analysis for Tracking an Object in WSN with TLS

In time slot Δt between time $i-1$ and i , considering that there are $k^{\wedge}(i)$ ($k^{\wedge}(i) \leq k(i)$) sensors that can detect the target, but only $k_q(i)$ ($k_q(i) \leq k(i)$) sensors would be queried by BS for detailed information.

$$\text{Number of sensors in the sensing state: } k\left(\frac{\sigma}{r_s}\right)^2 \ln \frac{1}{1-H}$$

$$\text{Number of sensors that detect the target: } k^{\wedge}(i) \quad (k^{\wedge}(i) \leq k(i))$$

$$\text{Number of sensors that need to generate DAT packets: } k_q(i)$$

$$\text{Number of sensors in the idle state: } N - k\left(\frac{\sigma}{r_s}\right)^2 \ln \frac{1}{1-H}$$

Energy consumption using TLS can be expressed as

$$E_i^{\wedge} = k\left(\frac{\sigma}{r_s}\right)^2 \ln \frac{1}{1-H} \varphi_s \Delta t + k_q(i)\varphi_aT_s + k^{\wedge}(i)\varphi_aT_r + (N - k\left(\frac{\sigma}{r_s}\right)^2 \ln \frac{1}{1-H})\varphi_i \Delta t$$

$$E = \sum_{i=0}^{t_{end}} E_i^{\wedge} \quad (8)$$

Therefore, the difference consumption $\Delta E_i = E_i - E_i^{\wedge}$ can be expressed as:

$$\begin{aligned} \Delta E_i &= (N - k\left(\frac{\sigma}{r_s}\right)^2 \ln \frac{1}{1-H})\varphi_s \Delta t + (k(i) - k^{\wedge}(i))\varphi_aT_r - (N - k\left(\frac{\sigma}{r_s}\right)^2 \ln \frac{1}{1-H})\varphi_i \Delta t \\ &= (N - k\left(\frac{\sigma}{r_s}\right)^2 \ln \frac{1}{1-H})(\varphi_s - \varphi_i)\Delta t + (k(i) - k^{\wedge}(i))\varphi_aT_r \\ \Delta E &= \sum_{i=0}^{t_{end}} \Delta E_i \end{aligned} \quad (9)$$

Since $\varphi_s < \varphi_i$ & $k(i) \geq k^{\wedge}(i)$ (Because AZ is a part of the sensor field), we can see that the energy consumption is greatly reduced with the passage of time.

The comparison between tracking flows with TLS and without TLS has been shown in this section. We can see that the energy consumption is greatly reduced through equation (9) if using TLS. In the next section, we will show simulation results and practical consideration.

5 Simulation and Practical Consideration

We present results for a case study carried out using MatLab6.1 and C++ in this section. The simulation is done on a 100m by 100m field grid with 20 sensors randomly placed in the sensor field.

The parameters of the prediction models are $\sigma = 10, \Delta t = 0.3s, H = 90\%$, $r_s = 15m$. We choose the energy consumption model parameters as $\varphi_a = 400nj/s, \varphi_i = 100nj/s$ and $\varphi_s = 1000nj/s$, we have no physical data available for T_r and T_s ; however, their values do not affect the target localization procedure, therefore we only need to set them manually to satisfy the relationship $T_r \prec T_s$. In this case, $T_r = 10ms, T_s = 100ms$.

The layout of the sensor field is given in Fig 2, with a target trace randomly generated in the sensor field. The target travels from the position (0, 0). We assume the target locations are updated at discrete time instants in unit of seconds, and the granularity of the time is long enough for sampling by two neighboring locations in the target trace with negligible errors. For simplicity, we have evaluated TLS for $k_q(i) = 1$. Fig 3 presents the instantaneous energy saving in percentage, and Fig 4 presents the energy consumption for the case study as the target moves along its trace in the sensor field. From Fig 3 and Fig 4, we note that a large amount of energy is saved during target localization. Averagely 80% energy could be saved if TLS has been used.

Fig. 1. Sensor Field with Target Trace

Fig. 2. Instantaneous Energy Saving in percentage

Fig. 3. Energy Consumption Comparison

Fig. 4. Prediction Model Analysis

Fig 5 shows how our prediction model works: there are four sensors needed to be woken up inside the dashed round that presents the AZ-19, while actually three of them

which are in the smaller round can detect the target at time 19. In our simulations, the prediction model has worked efficiently. (Here we use (4) to generate prediction points).

Practical consideration: In actual environment, according to our definition 3, we know that V_H follows:

$$\frac{R}{\Delta t} < V_H < \frac{R + r_s}{\Delta t} \quad (10)$$

Let us use some reasonable, common data to check V_H 's lower limit and upper limit, e.g: $H=0.9$

$$\begin{aligned} \sigma = 10 &\Rightarrow R = 21m, \Delta t = 0.3s, r_s = 40m \\ &\Rightarrow 70m / s < V_H < 200m / s \\ &\Rightarrow 252km / h < V_H < 720km / h \end{aligned}$$

We can see that V_H is large enough for the target we track in the actual applications.

The standard deviation σ in (1) can be gained using transcendental information about the target in actual applications, and we believe that σ is proportion to V_H .

The simulation results shown in this section indicate that TLS runs smoothly in the tracking procedure while reducing energy consumption by 80%.

6 Conclusion and Future Work

In this paper we bring forward an energy-efficient target localization scheme named TLS based on a prediction model for wireless sensor networks. The TLS make use of previous target position information and PDF knowledge of the target's trace to reveal which area the target will be in at the next moment, then a limited amount of sleeping sensors inside that area will be woke up to keep alert. We also propose a corresponding two-step communication protocol between sensors and BS. The analysis shows that TLS can effectively reduce energy consumption as the simulation results indicate. Since packets transferred in the procedure are kept very small, TLS decreases the latency for target localization as well.

In our future work, we will focus on improving the accuracy of the TLS. If the track knowledge mode we use cannot accurately model the actual track, there will be extra errors in the localization. We will study the properties of this kind of errors in our future work and try to propose an error-smooth method.

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Appendix

A. Proof of Theorem 1 and 2

Theorem 1. Given a threshold $H (0 \leq H \leq 1)$, $\exists R \geq \sigma \lfloor \sqrt{2 \ln \frac{1}{1-H}} \rfloor$, the probability that target will be in the round centered at prediction point (x_{pre-i}, y_{pre-i}) with radius R at time i is greater than H .

Proof: Assume that $P(x, y)$ is the probability that the target will be in the round centered at prediction point (x_{pre-i}, y_{pre-i}) with radius R at time i , according to (1):

$$P(x, y) = \iint_{(x-x_{pre-i})^2 + (y-y_{pre-i})^2 \leq R^2} f(x, y) dx dy. \text{ Given a threshold } H (0 \leq H \leq 1), \text{ if}$$

$$P(x, y) \geq H, \text{ which means that: } \iint_{(x-x_{pre-i})^2 + (y-y_{pre-i})^2 \leq R^2} f(x, y) dx dy \geq H, \text{ let } u = \frac{x - x_{pre-i}}{\sigma},$$

$$v = \frac{y - y_{pre-i}}{\sigma}$$

$$\Rightarrow \frac{1}{2\pi} \iint_{u^2 + v^2 \leq r_0^2} e^{-\frac{u^2 + v^2}{2}} du dv \geq H \Rightarrow r_0 \geq \sqrt{2 \ln \frac{1}{1-H}} \Rightarrow R \geq |\sigma| \sqrt{2 \ln \frac{1}{1-H}} \quad \square$$

Theorem 2. According to our pervious assumption: there are k sensors per πr_s^2 averagely. ($k \geq 1, k \in \mathbb{Z}^+$), if $V_i \leq V_H$, there will be at least one sensor inside Awakening Zone- i that can detect target at time i .

Proof: According to Figure 2, if there is a sensor that can detect the target, it is inside the shadow S :

$$S = r_s^2 \theta_1 - r_s^2 \sin \theta_1 \cos \theta_1 + R^2 \theta_2 - R^2 \sin \theta_2 \cos \theta_2$$

$$\theta_1 = \cos^{-1} \left(\frac{r_s^2 + l^2 - R^2}{2rl} \right) \quad \theta_2 = \cos^{-1} \left(\frac{R^2 + l^2 - r_s^2}{2Rl} \right)$$

Fig. 1. An Example of AZ and the Target

Since there are k sensors per πr_s^2 averagely, it is easy to know: $S^*k / \pi r_s^2 \geq 1$.

According to Definition 3, V_H is the result of equation (6) when $S^*k / \pi r_s^2 = 1$. So if

$V_i \leq V_H$, $S^*k / \pi r_s^2 \geq 1$ which means that at least one sensor can detects the target. $\square$

B. Explanations of Variables in Paper

Table 1. Explanations of variables appeared in the paper

$I_i(x_i, y_i)$	Target's position we detect at time i.	r_s	Detection range of sensors
k	Density of WSN	ϕ_a	Power value of a sensor in active state
ϕ_s	Power value of a sensor in sensing state	ϕ_i	Power value of a sensor in idle state
(x_{pre-i}, y_{pre-i})	Prediction position of the target at time i	V_{i-1}	target's instantaneous speed at time i-1:
σ	The standard deviation	$H(0 \leq H \leq 1)$	threshold
$R = \sigma \sqrt{2 \ln \frac{1}{1-H}}$	The radius of AZ	$l_{\max}$	$l_{\max} = V_H * \Delta t$
V_H	The maximum speed t	d	Distance between the sensor and the target
E_r	Rest energy	α	The percentage variable
F	decides whether the sensor would be queried by BS	$k_q(i)$	Number of sensors queried by BS at time i
$k(i)$	Number of sensors can detect the target at time i without TLS	$k^{\wedge}(i)$	Number of sensors can detect the target at time i with TLS
Δt	Time interval between time i-1 and i	E_i	Energy consumption between time i-1 and i without TLS
$E_i^{\wedge}$	Energy consumption between time i-1 and i with TLS	ΔE_i	Difference between E_i and $E_i^{\wedge}$