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Energy-Efficient Opportunistic Localization with Indoor Wireless Sensor Networks

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Abstract. Localization challenges researchers for its contradictive goals, i.e., how to tackle the problem of minimizing energy consumption as well as maintaining localization precision, which are two essential trade-offs in wireless sensor network systems. In this paper, we propose an Energy-Efficient Opportunistic Localization (EEOL) scheme to satisfy the requirement of positional accuracy and power consumption. We explore the idea of opportunistic wakeup probability to wake up an appropriate numbers of sensor nodes, while ensuring the high positional accuracy. Sensor nodes can be triggered by the opportunistic wakeup probability sent from the user. Through utilizing this method, the number of active sensors in the sensing range of the user is decreased, and the power consumption is significantly reduced. Theoretical analysis has been presented to evaluate the performance of EEOL. Simulation results show that EEOL confirms our theoretical analysis.

Keywords: Indoor Localization, Energy Efficiency, Wireless Sensor Network, Opportunistic Localization.

1. Introduction

As a new technology of information collection and dissemination, Wireless Sensor Network (WSN) has greatly extended our ability in target tracking, monitoring, intrusion detecting and other localization applications [1]. It has aroused great concern and been widely used in national defense, national security, environmental monitoring, traffic management, health care, manufacturing, antiterrorism and other disaster areas.

Localization is an inevitable challenge when we deal with sensor nodes. It is a problem that has been studied for many years. Without the nodes' position information, the monitoring information is always meaningless in the

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applications of WSNs. Consequently, a variety of WSN systems [2-4] for indoor localization have been developed and well tested.

In all these applications, energy consumption is one of the most important issues [5]. For sensor nodes in small size, energy is restricted and it is not convenient to charge or change batteries. As a result, it requires the power consumption to be as little as possible to extend the network's lifetime. And, how to take full advantage of the energy to maximize the network's efficiency has become one of the primary challenges for sensor networks. Nevertheless, power management in WSNs remains to be a difficult problem and it is unlikely to be solved in the near future, since the progress in battery capacity is slow. Several research issues remain to be solved before applications such as military tracking, environmental monitoring and positioning become economically practical.

Experimental results have shown that the energy consumption of wireless devices in the idle state is slightly less than that in transmitting and receiving states. As a result, an important approach to reduce power consumption is to switch the nodes into the low-power sleep mode as long as possible. There is an effective approach proposed for saving the power of sensor nodes using the duty cycling policy in [6]. It is true that many methods have been proposed in the literature, but most existing protocols need to wake up sensors periodically. Hence, as for localization, certain amount of energy is still wasted by using unnecessary sensors. Basically, we can use only two or three sensors to locate an object based on the technique of localization, and thus the power of other active sensor nodes could be saved. Therefore, it would be a proper approach to balance the requirements of positional accuracy and the power consumption restrictions by waking up an appropriate number of sensor nodes.

Opportunistic computing model motivates the basic idea of the relationship between the number of sensor nodes and the positional accuracy, which is the key to balancing power consumption and positional accuracy. Based on the opportunistic computing model, we propose an Energy-Efficient Opportunistic Localization (EEOL) scheme that regulates the sensors' on-off states through changing the wakeup probability of each sensor dynamically, according to the number of the sensors. Furthermore, it ensures that the number of active sensor nodes is large enough for the localization techniques, Trilateration algorithm for example.

Our proposed approach aims at obtaining the appropriate number of active sensors to locate an object in the process of localization, and avoiding unnecessary waste of energy. As for the total network efficiency, the power consumption significantly decreases and the network performance is improved. In a word, we achieve the purpose of reducing power consumption while ensuring the positional accuracy.

The rest of this paper is organized as follows. In Section 2, we discuss related work from the literature, presenting the context for our work. Section 3 provides our assumptions, scenarios and notation descriptions. Then, we describe our EEOL algorithm in Section 4. Simulation results are given in Section 5. Finally, Section 6 concludes the paper.

2. Related Work

The basic concept of WSN and its localization algorithms have been the subject of many research studies recently. Here, we focus mainly on the WSN indoor localization systems and energy-efficient localization algorithms.

2.1. WSN indoor localization systems

Numerous works have already analyzed the performance of WSN indoor localization systems over the past decades, [7] for example, during which, new systems are being developed continuously.

Lots of the existing indoor localization systems are based on range-based schemes that exploit e.g. the Received Signal Strength (RSS) technology. The localization technique mentioned in [3] can achieve high accuracy and stability in indoor environment. MMSE proposed in [4] can minimize the localization errors. Additionally, the Dual-modal Indoor Mobile Localization System [8], which was implemented using the RSS approach and the unscented Kalman filter (SPKF) algorithm in active and passive dual-modal architecture, decreases the system cost and simplifies the sensor deployment. Further, WAX-ROOM in [9] incorporates three different localization techniques, namely a plain-RSS technique, a SA-RSS technique, and the range-free APIT algorithm, as well as an Optimal Fusion Rule (OFR) in order to leverage localization accuracy.

There are many other techniques for indoor localization. LOcalization of Sensor Nodes by Ultra-Sound (LOSNUS) [10] offers a high accuracy of 10 mm, a locating rate up to 10 cycles/s, and it is applicable for both tracking mobile and locating static devices. The Crickets motes use the Time Difference of Arrival (TDoA) between the RF and the ultrasound signals to estimate the distance of the object. In [2] a system consisting of Cricket wireless sensor motes, a camera and a Pan/Tilt gimbal was proposed to solve the indoor localization and surveillance problems.

2.2. Energy-efficient localization

Energy consumption is one of the most important issues we concern in recent years. A number of methods have been proposed to address the energy efficiency problem.

A localization algorithm based on particle filtering for sensor networks was proposed in [11]. It is assisted by multiple transmit-power information, which outperforms the existing algorithms that do not utilize multiple power information.

Given a specified positional error tolerance in an application, the sensor-enhanced, energy-efficient adaptive localization system [12] dynamically sets sleep time for the sensors, adapting the sampling rate of target's mobility level. It achieves better energy saving while conforming to application's error tolerance. However, the process of error estimation dynamically depends on several factors in the environment.

LPL (Low-Power Scheme for Localization) [13] and OLP (Optimized Listening Period) [14] explore decreasing the idle listening and an optimized allocation of the localization tasks on the nodes. In LPL, the mobile nodes (MNs) transmit packets and the anchor nodes (ANs) take RSSI measurements. During the transmissions, the MN goes into sleep mode to save energy. While in the OLP, the ANs are synchronized and transmit packets to the MNs in a short time. OLP was designed to keep the inter-arrival time of the transmitted packets as short as possible and reduce the idle listening time in the MN. Nonetheless, for large scale sensors networks, the energy consumption is still significant.

In [15], the presented scheduling algorithm selects a subset of active reference nodes to be used in localization, which serves to reduce the message overhead, increase network lifetime, and improve localization accuracy in dense mobile networks. The key for the decision of reference nodes is the design parameter which describes the average density required to ensure localization accuracy with high probability. Reference nodes remain active for several seconds. After that, all devices wake up and new references can be selected. However, maximizing the nodes' sleep time that the nodes never wake up until the reception of wakeup messages is much more energy efficient.

In the algorithms mentioned above, the duty cycle of the sensor nodes is fixed in advance. While in [6], an innovative probabilistic wakeup protocol is proposed for energy-efficient event detection in WSNs, the central idea of which is to reduce the duty cycle of every sensor via probabilistic wakeup, exploiting the dense deployment of sensor networks.

Our idea is initially inspired by the selection of the subset of active nodes and the probabilistic wakeup protocol. We have studied existing localization techniques [16]. According to the Trilateration algorithm, three sensors can locate a target, and the more the sensors, the more accurate the localization will be. In our study, we aim at reducing the number of the active sensors by employing opportunistic wakeup probability to save power consumption as well as satisfying the requirement of positional accuracy. Inspired by the idea of opportunistic computing as well, we manage to reduce the massage communication between the sensor nodes and the mobile target, which also contributes to energy saving.

3. Problem Description

In this paper, we consider a wireless network composed of *n* randomly deployed nodes, and each of them is aware of its own position. All sensor nodes in the network are distributed randomly in a two-dimensional indoor environment, which are initialized to sleep state at the beginning. Assume that one mobile node, called *User*, is moving freely, in need of localization service. However, the *User* can only be located by the active sensor nodes. The sensors will be waked up by the wakeup probability. Nodes are equipped with radio transmitters/receivers for communications. By using RSS or time of arrival (TOA) of radio signals, nodes can estimate the distance to the *User*.

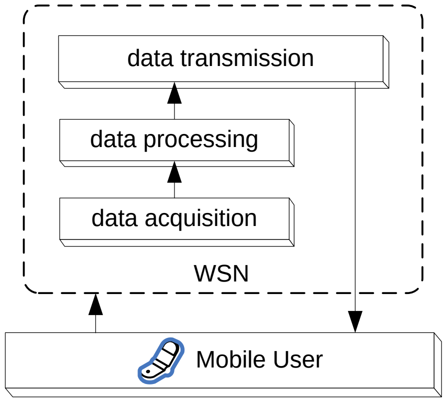

Fig. 1. A localization system

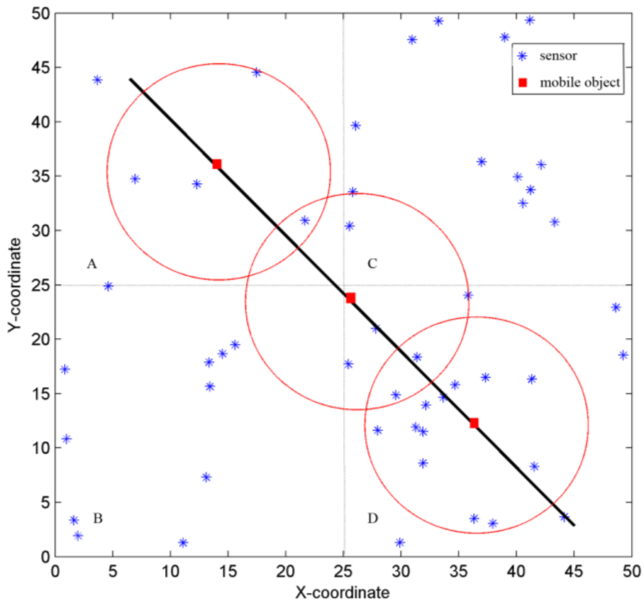

Fig. 2. A scenario of locating a mobile object with 50 distributed sensor nodes

Our localization system is shown in Fig.1. The mobile *User* (who uses a PDA or mobile phone with wireless sensors) comes into the network and calls for the localization service. After the process of data acquisition and data transmission, the localization algorithm is implemented to compute the required location. Then the User gets its own location information, using the returned data from the network.

In the Data Acquisition Phase, we need to measure the distance between the object and the nodes. Then, here comes the problem. As shown in Fig. 2, when the mobile object is moving in places like Region D, since there are more sensor nodes around than Region A, some nodes are redundant according to the Trilateration algorithm, which means a waste of energy. If we shut down the unnecessary sensor nodes while ensuring the number of sensor nodes $n \geq 3$, it will be a significant contribution for reducing the power consumption of the entire sensor network.

In this paper, we try to develop a method to control the number of sensor nodes in the sensing range of the mobile object to achieve our goal of minimizing power consumption. Our proposed method is based on the following assumptions:

- The number of active sensors around the mobile object n is large enough ($n \geq 3$), then the object can be accurately positioned without considering other environmental factors;
- Once the sensor node wakes up, all parts of the sensor are active, including the sensor data processing unit, sensing devices, data transmission equipment, data receiving device and system clock ;
- In the sleep state, the sensor nodes can exchange opportunistic data, so that it can regulate its on and off states to complete localization;
- The sensor nodes, in the sensing range of the User, are independent, in other words, waking up a sensor will not affect the on or off rate of other sensors.
- The sensing range of the sensor nodes is the same with that of the sensor embedded in the User;
- The wakeup probability sent to the sensor nodes within the sensing range of the mobile object, is the same;
- There is only one User.

4. Energy-Efficient Opportunistic Localization

In this section, we will propose the Energy-Efficient Opportunistic Localization (EEOL) scheme. The work flow of the algorithm is depicted in Fig. 3. Our scheme uses the opportunistic wakeup probability based on the opportunistic computing model to schedule the sensors' on-off states and to obtain an appropriate number of active sensor nodes to locate the User. Naturally, the Data Acquisition Phase is the focus of this paper, and the appropriate number of sensors is the key to the problem.

We will first explain how the opportunistic wakeup probability makes contribution to power saving, as well as the relationship between opportunistic wakeup probability and the number of sensor nodes.

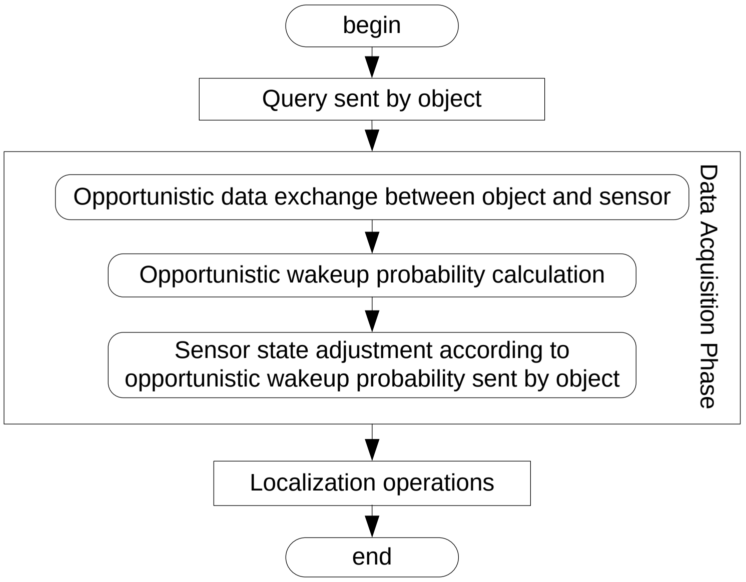

Fig. 3. Work flow of the localization system

Researchers have developed lots of protocols and algorithms in order to extend lifetime of the system and to maintain the positional accuracy. Typically, sensors can be divided into three modes according to their working status: active mode, sensing mode and sleep mode [6]. Previous research shows that for the sake of maximizing power savings, an optimal way is to set duty cycle for the system in which sensors turn on or off periodically.

Setting a fixed value of duty cycle ratio δ to turn each sensor node on or off periodically is fairly easy to implement. However, a defect of this method is that a sensor will still periodically turn on or off even when there is no event occurs, which is not flexible enough and might lead to a waste of energy.

According to the localization techniques, the more the sensors, the more accurate the localization will be. When more sensor nodes are detected in the User's sensing range (hereinafter referred to as in-sensors), the wakeup probability is smaller, provided that the positional accuracy can be ensured. Hence, we exploit the opportunistic wakeup probability instead of static duty cycle, so that the sensor nodes can decide by themselves whether to wake up or to continue to sleep.

4.1. Energy-efficient localization

Every node in the network is equipped with a common wireless communication interface that is used for (opportunistic) data exchange. The radio transmission is always correctly received within a distance *R* (coverage range) from the transmitter, whereas it might not be correctly received from longer distances. Therefore, opportunistic data exchange requires the nodes to be mutually in range. Assume that opportunistic data exchange immediately takes place as soon as both conditions are met. Such an event is coined rendezvous [17].

When the User goes into the coverage range of the nodes, messages will be exchanged between the nodes and the object. The object becomes aware of the number of sensor nodes within its sensing range by the messages received from the nodes, which will be used for the calculation of opportunistic wakeup probability.

4.2. Opportunistic wakeup probability calculation

According to the Trilateration localization algorithm, in two-dimensional space, we need at least three reference nodes' location information to locate an object. Because we assume that the nodes are independent, when the number of in-sensors $n \geq 3$, the probability of successfully locating a User obeys the binomial probability B(n, p), where n represents the number of sensor nodes in the sensing range of the mobile object, and p represents the wakeup probability of sensor node. The probability of accurately locating a moving object can be obtained from (1).

$$P(K \geq 3) = 1 - P(K = 0) - P(K = 1) - P(K = 2) \quad (1)$$

$$P(K \geq 3) = 1 - C_n^1 p(1-p)^{n-1} - C_n^2 p^2 (1-p)^{n-2} - (1-p)^n \quad (2)$$

where P represents the probability of accurately locating the mobile object, and K represents the number of sensor nodes to wake up. According to (2), we can map out the quantitative relation between the number of in-sensors and the probability of accurately locating a User, under certain preconditions of each sensor's wakeup probability.

From Fig. 4 we can easily see that, given a certain number of in-sensors, the higher the wakeup probability, the higher the accurate positioning probability. On the other hand, given a certain positional accuracy, the more in-sensors, the lower the wakeup probability and the more the power can be saved. Consequently, setting the number of in-sensors reasonably for the User will achieve energy-efficient localization while ensuring accuracy.

For different applications, the positional accuracy is different. At any time, the probability of positioning a User must satisfy the lowest positional accuracy λ, as Eq. (3) shows.

$$P(K \geq 3) \geq \lambda \quad (3)$$

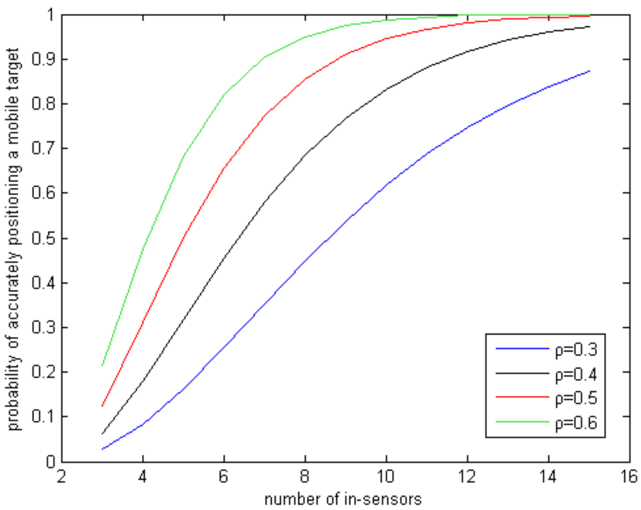

Fig. 4. Relationship between probability of accurate positioning and number of in-sensors

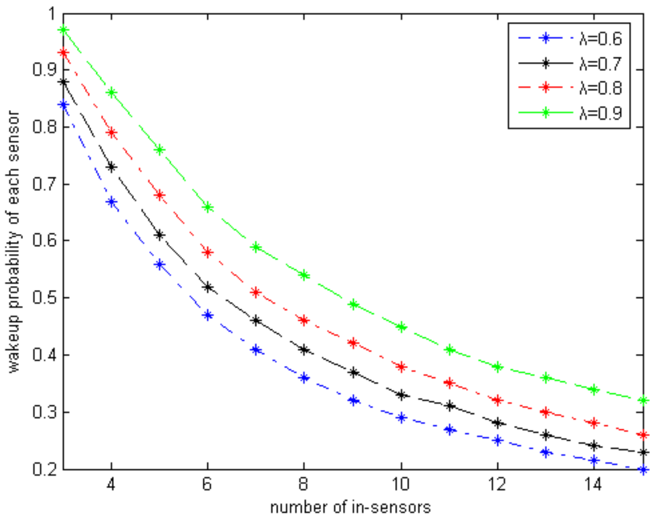

Fig. 5. Relationship between sensor wakeup probability and number of in-sensors

Based on (2) and (3), we get the numerical relations between the number of in-sensors and the wakeup probability which is shown in Fig. 5. In Fig. 5, with the increase of the number of in-sensors, the wakeup probability of each sensor decreases. It can be found that the relationship between the number of in-sensors and the wakeup probability fits the features of the exponential distribution function. In order to make this wakeup probability easier to be applied in indoor localization systems, we conduct some simulations to obtain the functional relationship between the wakeup probability and the number of in-sensors.

We use MATLAB curve fitting technique to get the relation between the wakeup probability and the number of in-sensors when λ =0.8. After fitting, it gives a very satisfactory fitting result with the exponential distributions of 95% confidence intervals. The residual is the difference between the real value and the estimated value. In Fig. 6, we can see that the basic residual is in (-0.005, 0.005), which has already achieved a good degree of fitting.

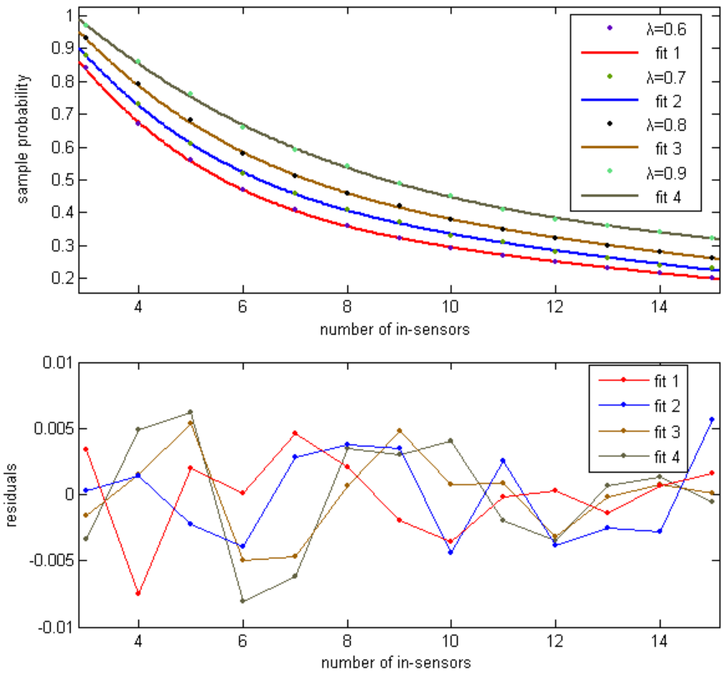

Fig. 6. Results of fitting

Table 1. Coefficients VS positional accuracy

Coefficients	Positional Accuracy			
	λ =0.6	λ =0.7	λ =0.8	λ =0.9
a_1	3.274	3.299	3.893	2.866
b_1	-7.647	-8.713	-10.66	-12.46
c_1	7.459	8.19	9.229	11.76
a_2	0.5796	0.6304	0.6999	0.7464
b_2	-12.8	-12.65	-14.05	-29.78
c_2	26.83	27.16	29.09	47.62

Accordingly, the wakeup probability can be computed as follows:

$$\eta = a_1 e^{-\frac{(n-b_1)^2}{c_1^2}} + a_2 e^{-\frac{(n-b_2)^2}{c_2^2}} \tag{4}$$

We derive (4) from MATLAB, where a_1, a_2, b_1, b_2, c_1, c_2 are coefficients which might vary with λ. Simulation results show that Equation (4) is the most acceptable fitting, compared with other fitting formulas. Therefore, we use the same formula to fit others. Fig. 6 shows the results of fittings.

Using the data in Table 1, we can dynamically calculate the wakeup probability of the sensor nodes according to the number of in-sensors. That is, if positional accuracy λ is known, we can check Table 1 to derive a_1, a_2, b_1, b_2, c_1, c_2, and then we can get the wakeup probability using (4).

4.3. Sensor state adjustment

Sensor nodes are initialized to sleep state at the beginning. They will never wake up until the reception of wakeup probability from the User. The decision of wakeup is defined as the comparison between the wakeup probability and a random number between (0, 1).

When nodes wake up, they begin to measure the distance between the *User* and themselves and transmit it back to the *User*. After that, the User calls the localization algorithm, such as Trilateration Algorithm, Maximum Likelihood Estimation Method, etc. to compute the required location, using the returned data from the sensors, and then obtain its own location information.

5. Performance Evaluation

The performance of the EEOL scheme will be evaluated through a series of simulations. We use a bounded region of 100 x 100 m^2, in which nodes are placed using a uniform distribution. Additionally, we use an average value, 24mW, as the working power. A number of experiments have been conducted to assess the effectiveness of the proposed algorithm by using the MassMobility model. Table 2 lists the parameters used for simulation.

We compare our EEOL scheme with the existing method using duty cycle (DC) policy, in terms of the average energy consumption and the ratio of effective positioning.

We conduct simulations to locate the target using 100 sensor nodes whose communication range is set to 20m. As shown in Fig. 7 and Fig. 8, the energy consumption increases linearly with time. We can observe the energy consumption of DC is significant, which is nearly 80% larger than that of EEOL. This is mainly because the sensor nodes keep sleeping when the target is outside its sensing range. In Fig. 8, it is clear that the smaller the duty cycle, the less the energy consumption. Fig. 9 depicts the effective positioning ratios of both EEOL and DC. As we can see, the ratio of effective positioning of EEOL is as large as 60%~90%. In contrast, when the duty cycle is 20%, the network of DC is only capable to locate the target in 20% of the total time. When the duty cycle is 2%, 5% or 10%, the ratio will be less than 5%.

Table 2. Simulation settings

Parameter	Value
Number of Nodes	25,50,75,100
Area Size	100×100 m^2
Simulation Time	1000s
Communication Range	20,30,40,50
Accuracy (λ)	0.6,0.7,0.8,0.9
Duty Cycle (δ)	2%,5%,10%,20%
Cycle	10s
Power	24mW
Speed	5
Change Angle	5

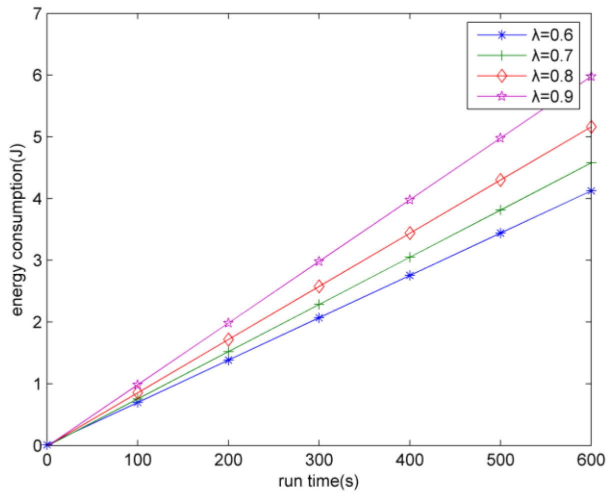

Fig. 7. Energy consumption with EEOL using 100 sensor nodes

5.1. Impact of number of sensor nodes

To examine the impact of different numbers of sensor nodes, we set the number of nodes to 25, 50, 75 and 100 respectively. We take λ=0.8 and

δ =10% as an example for EEOL and DC. Fig. 10 and Fig. 11 show the results of our simulation, where the communication range is 20m.

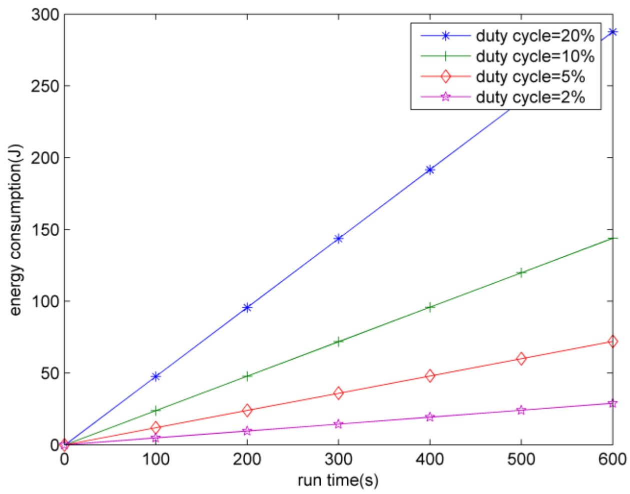

Fig. 8. Energy consumption with DC using 100 sensor nodes

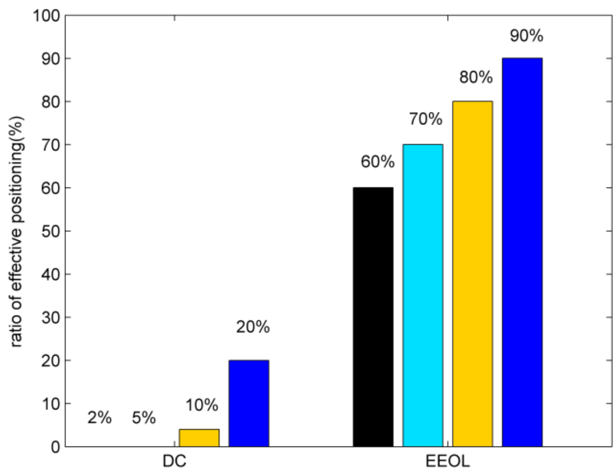

Fig. 9. Ratios of effective positioning for DC and EEOL

As shown in Fig. 10, we focus on the energy consumption at the moment of 200s and 400s. Compared with EEOL, DC performs worse, which can also be proved in Fig. 7 and Fig. 8. We can easily observe that with the increase of the number, the energy consumption drops down.

Fig. 11 shows the ratio of effective positioning with different number of sensors. Our EEOL algorithm significantly outperforms the DC method. With 25 to 75 nodes, the ratio of effective positioning of DC is close to 0, while it become up to 80% under EEOL. A low density of sensor nodes may lead to a low ratio of effective positioning.

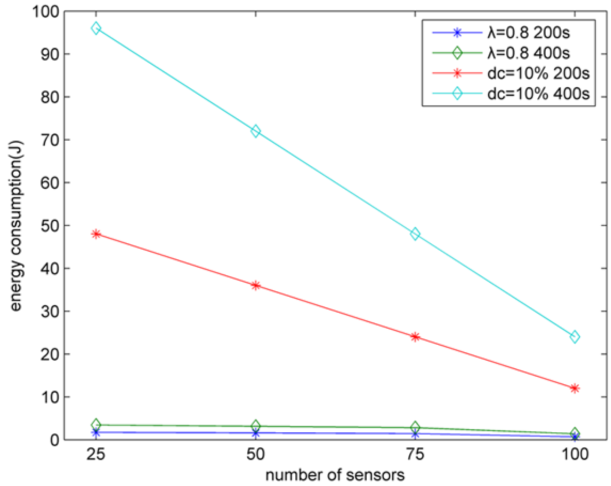

Fig. 10. Energy consumption versus number of sensor nodes

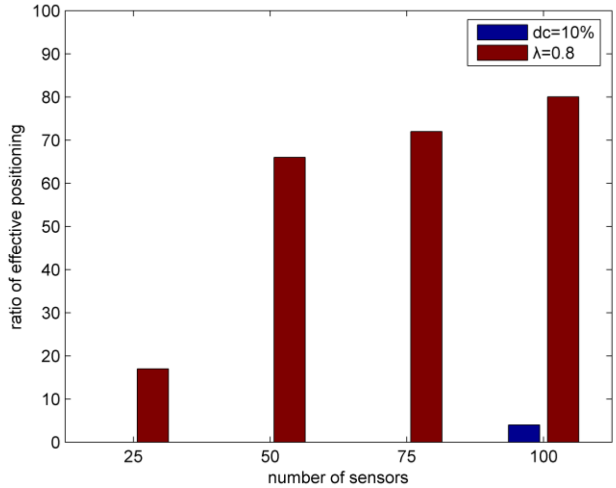

Fig. 11. Ratio of effective positioning versus number of sensor nodes

5.2. Impact of communication range

We conduct simulations with 100 sensor nodes, using different communication ranges. Here we also take λ =0.8 as an example for EEOL, and focus on the energy consumption at the moment of 200s and 400s. Fig. 12 and Fig. 13 show the simulation results.

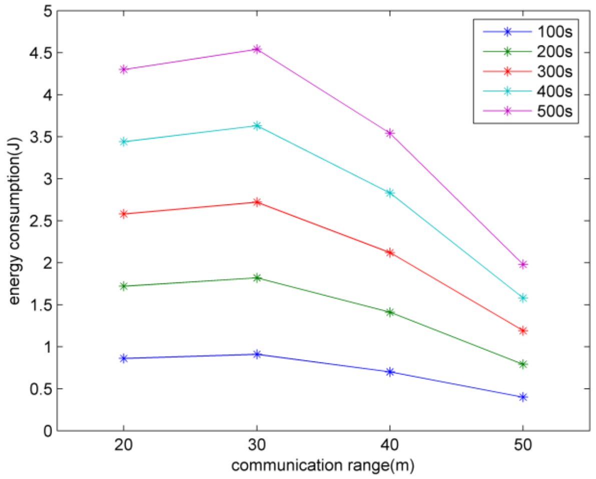

Fig. 12. Energy consumption versus communication range

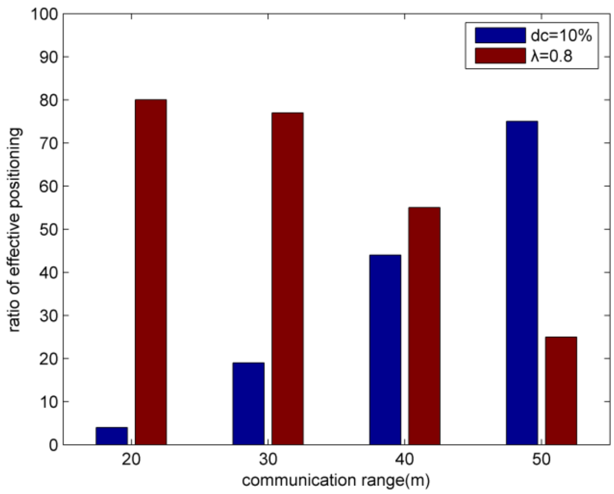

Fig. 13. Ratio of effective positioning versus communication range

It is clear that the communication range can not affect the energy consumption of DC, so we do not show it in Fig. 12. As we can see, the energy consumption decreases as the communication range increases from 30m to 50m. Fig. 13 shows the ratios of effective positioning for different communication ranges. With the increase of the communication range, the ratio of effective positioning for EEOL will decrease. As for DC, the larger the duty cycle, the larger the ratio of effective positioning will be. This is reasonable since there are more sensor nodes in the sensing range of the target if the communication range is larger.

6. Conclusions

In this paper, an energy-efficient method for indoor localization (namely EEOL) has been proposed to reduce energy consumption, which can be easily applied in indoor localization systems. To balance the energy efficiency and the requirement of positional accuracy, we use opportunistic wakeup probability policy to wake up an appropriate numbers of sensor nodes. However, since most existing protocols need to wake up sensors periodically to perform positioning, certain amount of energy is still wasted by unnecessary sensors. As for localization, only two or three sensors are necessary based on the technique of localization to locate an object. Sensor nodes that are not triggered by opportunistic wakeup probability provided by the User keep sleeping. We avoid the communications between sensors, so that the sensor nodes are independent from each other, which will also make contribution to reducing the power consumption. We used MATLAB to simulate the relation between the number of sensor nodes and positional accuracy. By switching more sensors to sleep mode, the power is saved, and the lifetime of the localization network is prolonged. Simulation results are presented to demonstrate the performance of EEOL.

Possible further work includes the following topics: firstly, to produce a more practical investigation to satisfy the need of the positional accuracy; secondly, how to adapt our algorithm if there are multiple Users in a more complex environment; thirdly, how to tackle the issue of locating a mobile User if there are insufficient sensor nodes or network disconnection occurs.

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