A Self-Adaptive Approach for Mobile Wireless Sensors to Achieve Energy Efficient Information Transmission

XING SU, ZHI CAI, XIBIN JIA, LIMIN GUO, AND ZHIMING DING
Faculty of Information Technology, Beijing University of Technology, Beijing 100124, China

ABSTRACT
Wireless sensor networks have played an important role in many applications, where sensors in the network can automatically collect and transmit information in an environment without much human maintenance. To enhance the adaptability of sensors, people produce mobile wireless sensors through fixing wireless sensors on mobile vehicles or robots. The same as static wireless sensors, since the energy of mobile wireless sensors is still supplied by the battery, their energy management has a great impact on their lifetime. Different with static wireless sensors, the mobility of mobile wireless sensors gives us a new perspective to achieve the efficient energy management. In this paper, a decentralized self-adaptive approach is proposed for mobile wireless sensors, which enables sensors in a mobile wireless sensor network to adapt their locations according to the information transmission regularity in the network so as to reduce their energy consumption for the information transmission. The experimental results indicate that after employed the proposed approach to adapt locations, the energy consumption for the information transmission of sensors in a mobile wireless sensor network can be greatly reduced and their lifetime is extended.

INDEX TERMS
Energy efficiency, information transmission, mobile wireless sensor network, self-adaption.

I. INTRODUCTION
Nowadays, due to the low infrastructure dependence, adaptability, scalability, etc., wireless sensor networks (WSNs) have played an important role in many applications, such as intelligent transportation, environment monitoring, health care, military, etc. [2]–[4], [15], [17]. In these applications, a number of sensors are deployed in a target environment, where they can sense to collect the information of the environment. Then, sensors can use wireless transceivers to transmit their collected information to receivers or sinks. Through WSNs, people, such as researchers, managers, etc., can obtain the information of an environment without entering it. However, this working mode means that wireless sensors have to work in an environment for a long period of time without human maintenance. Since the energy of sensors is only supplied by the battery, how to effectively manage the limited available energy of sensors for the information collection and transmission is a key issue in WSNs.

In WSNs, the energy of sensors is mainly consumed for the information collection (sensing) and transmission. By contrast, the energy consumed for the information collection is much less than that consumed for the information transmission. At the early stage of the WSN, sensors transmit their collected information directly (or through satellites) to receivers or sinks [5]. This type of WSNs is called unconnected WSNs. Based on the wireless communication technology, the energy consumption for the information transmission is proportional to the square of the information transmission distance so the energy consumption for the information transmission in unconnected WSNs is huge. In order to reduce the energy consumption, many approaches were proposed from different perspectives. One kind of approaches are through establishing connected WSNs [12], [13], [22]. In connected WSNs, sensors use their neighboring sensors to transmit information to receivers or sinks in a multi-hop way, which
can greatly reduce the information transmission distance so as to save the energy of sensors for the information transmission. Rogers et al. [11] proposed a self-organized routing approach for WSNs, which enables sensors to automatically choose the most suitable neighboring sensors to transmit information. In recent years, many relay-based approaches are proposed, which reduce the information transmission distance through deploying relays at suitable locations in a WSN [5], [18], [22]. In these approaches, relays act as temporary receivers or sinks, which collect information from nearby sensors and transmit it to the final receivers or sinks.

All above energy efficient approaches are proposed for static WSNs, where sensors in the WSN cannot move. In order to enhance the adaptability of WSNs, people produce mobile wireless sensors through fixing wireless sensors on mobile entities. The network consisting of this kind of sensors is called the mobile wireless sensor network (MWSN). In MWSNs, sensors can dynamically adapt their locations according to the requirement of environments and other sensors in the network, which makes MWSNs more adaptive than static WSNs. In addition, the adaptability of MWSNs creates a new perspective for sensors to achieve the efficient energy management. In this paper, the mobile wireless sensors indicate the agents that can collect (sense) and transmit information, such as vehicles with information collection and transmission devices, persons with information transmission devices, etc. Mostly, the resources for mobile wireless sensors to move and information handling are not the same and cannot be shared. Therefore, like other researches on mobile wireless sensors, the energy management only considers the energy consumption for the information transmission devices and we do not consider the energy consumption for their mobility. However, in the recent years, the approaches proposed for MWSNs mainly focus on the use of sensors’ mobility to route or self-organize in complex environments and barely pays attention to reduce the energy consumption of sensors [7], [14], [16]. This is because that the energy consumption problem of sensors in MWSNs can be partially solved by approaches proposed for static WSNs.

Against this background, the motivation of this research is to use of the mobility of sensors in MWSNs to reduce their energy consumption for the information transmission. In this paper, a decentralized self-adaptive approach is proposed for sensors in MWSNs, which enables them to adapt their locations according to the information transmission regularity in the MWSN so as to reduce their energy consumption for the information transmission. The contributions of the proposed approach are described as follows.

1) The proposed approach considers the characteristics of MWSNs, which enables sensors with local views about the MWSN to adapt their locations in a decentralized manner;
2) The proposed approach contains an optimization method, which enables sensors to quickly find their adaptive locations;
3) The proposed approach considers the shrink problem of MWSNs during the location adaption of sensors, which contains a compensation mechanism to handle such problem;
4) The proposed approach introduces a token based outside-in adaption mechanism and the adaptive threshold to enable sensors in a MWSN to efficiently adapt their locations in real applications.

The rest of this paper is organized as follows. Section II gives the problem description and definitions of the proposed approach. Section III describes the basic principle of the proposed approach. Section IV gives the experimental results and analysis. Section V introduces and analyses the related work of the proposed approach. Section VI is the conclusion and future work.

II. PROBLEM DESCRIPTION AND DEFINITIONS

In this section, we first use an example to describe the motivation of the proposed approach; Then, the formal definitions are given in Subsection II-A; Based on the definitions, the problem handled by this paper is described in Subsection II-B.

In a connected MWSN, mobile wireless sensors have their regular information transmission routings, which uses their wireless connections with neighboring sensors to transmit information to receivers or sinks in a multi-hop way. During the information transmission of a sensor, the information transmitting through different neighboring sensors are different, where the amount of information transmitted to some neighboring sensors are much more than that transmitted to other neighboring sensors. Since the energy consumption for the information transmission is proportional to the square of the information transmission distance [11], sensors in a MWSN should adapt their locations according to their information transmission regularity. By reducing their distance to the neighboring sensors that transmit a big amount of information, sensors can reduce their energy consumption for the information transmission.

As the example shown in FIGURE 1(a), a sensor $s_1$ has three neighboring sensors $s_{11}$, $s_{12}$ and $s_{13}$. The information transmission regularity between $s_1$ and $s_{11}$, $s_{12}$, $s_{13}$ is that $s_1$ transmits 1000 bytes information with $s_{11}$, 100 bytes information with $s_{12}$ and 10 bytes information with $s_{13}$. To reduce the...
energy consumption for information transmission, \(s_1\) should adapt its location to reduce its distance with \(s_{11}\), which is shown as FIGURE 1(b).

**A. DEFINITIONS**

In a connected MWSN, there are \(m\) number of mobile wireless sensors, which are \(S = \{s_1, s_2, \ldots, s_m\}\), where \(s_i\) represents the \(i^{th}\) sensor in the MWSN.

**Definition 1:** A mobile wireless sensor \((s_i)\) can be defined as follows.

\[
s_i = \langle id, loc_i, NSen_i \rangle,
\]

where \(id\) is the unique identification of \(s_i\) in the MWSN, \(loc_i = (x_i, y_i)\) represents the current location of \(s_i\) and \(NSen_i = \{s_1, \ldots, s_m\}\) is all neighboring mobile wireless sensors of \(s_i\), with which \(s_i\) can transmit information and \(s_{ij}\) represents the \(j^{th}\) neighboring mobile wireless sensor of \(s_i\).

In order to record the information transmission regularity for the location adaption, each sensor (e.g., \(s_i\)) needs to maintain its information transmission records, which can be described as \(ITr_i = \{itr_{i1}, \ldots, itr_{im}\}\), where \(itr_{ij}\) represents the information transmission record of \(s_i\) with its \(j^{th}\) neighboring mobile wireless sensor (i.e., \(s_{ij}\)).

**Definition 2:** An information transmission record of \(s_i\) \((itr_{ij})\) can be defined as follows.

\[
itr_{ij} = \langle loc_{ij}, a_{ij} \rangle,
\]

where \(loc_{ij} = (x_{ij}, y_{ij})\) is the current location of \(s_{ij}\) and \(a_{ij}\) represents the amount of information that is transmitted in bytes.

Based on the information transmission record of \(s_i\), all information transmission records of a MWSN can be described as \(\{ITr_1, ITr_2, \ldots, ITr_m\}\), which have duplicated information transmission records, because for an information transmission, both the sender (sensor) and the receiver sensor generate the information transmission records. But this does not affect the location adaption of sensors based on the proposed approach.

**B. THE PROBLEM DESCRIPTION**

The proposed approach aims to reduce the energy consumption for the information transmission of sensors through adapting their locations to reduce their distances to the neighboring sensors that transmit a big amount of information. The energy consumption for the information transmission is proportional to the square of the information transmission distance [11]. To evaluate the energy consumption for the information transmission of sensors in a MWSN, the object value (i.e., \(obj(S)\)) of the proposed approach calculated based on the Euclidean distance is described as follows

\[
obj(S) = \sum_{i=1}^{m} \sum_{j=1}^{NTR} ((x_i - x_{ij})^2 + (y_i - y_{ij})^2) \cdot a_{ij},
\]

where \(m\) is the number of sensors in the MWSN, \((x_i, y_i)\) is the current location of mobile wireless sensor \(s_i\), \((x_{ij}, y_{ij})\) is the current location of a \(s_j\)’s neighboring mobile wireless sensor \(s_{ij}\) and \(a_{ij}\) is the total amount of information transmission between \(s_i\) and \(s_{ij}\). The object of the proposed approach is to minimize the object value of the MWSN (i.e., \(min(obj(S))\)).

**III. THE BASIC PRINCIPLE OF THE PROPOSED APPROACH**

The proposed approach enables sensors with only local view about the MWSN to adapt their locations according to their information transmission regularity so as to reduce their energy consumption for the information transmission. In this section, first, the overview of the proposed approach is illustrated and described in Subsection III-A. Then, an optimization method to reduce the energy consumption of sensors is proposed in Subsection III-B. After that, the shrink problem caused by the optimization method and a compensation mechanism to handle the shrink problem are introduced in Subsection III-C. Finally, the token based outside-in adaption mechanism and the adaptive threshold for the real application of the proposed approach are introduced in Subsection III-D.

**A. THE OVERVIEW OF THE PROPOSED APPROACH**

In general, the proposed approach is an iteration process, which includes two steps: 1) The data collection and 2) the location adaption. In the data collection, the sensors need to collect the information transmission data between them and their neighboring sensors; According to the collected information transmission data, sensors will adapt their locations based on the proposed optimization method and the compensation mechanism, so as to reduce their energy consumption for the information transmission.

**B. THE OPTIMIZATION METHOD FOR THE SENSOR LOCATION ADAPTATION**

In the proposed approach, the object function of the MWSN is minimized through minimizing the object function of each sensor, which is described as follows.

\[
min(obj(S)) = \sum_{i=1}^{m} min(obj(s_i)),
\]

where \(m\) is the number of sensors in the MWSN. The object value of a sensor \(s_i\) in the MWSN is calculated as follows.

\[
obj(s_i) = \sum_{j=1}^{n} ((x_i - x_{ij})^2 + (y_i - y_{ij})^2) \cdot a_{ij},
\]

where \(n\) is the number of information transmission records of \(s_i\), \((x_i, y_i)\) is the location of \(s_i\), \((x_{ij}, y_{ij})\) is the current
location of a of $s_i$’s neighboring mobile wireless sensor $s_j$, whose information transmission with $s_i$ is recorded in $itr_{ij}$ (see, Definition 2) and $a_{ij}$ is the total amount of information transmission between $s_i$ and $s_j$.

The minimization of Equation 6 can be described as follows.

$$
\begin{align*}
\min (obj(s_i)) &= \min \sum_{j=1}^{n} ((x_i - x_j)^2 + (y_i - y_j)^2) \cdot a_{ij} \\
&= \min \left( x_i^2 + y_i^2 \right) \sum_{j=1}^{n} a_{ij} - 2x_i \sum_{j=1}^{n} x_j \cdot a_{ij} \\
&\quad - 2y_i \sum_{j=1}^{n} y_j \cdot a_{ij} + \sum_{j=1}^{n} (x_j^2 + y_j^2) \cdot a_{ij},
\end{align*}
$$

(6)

Since the current locations $(x_i, y_i)$ of all neighboring sensors of $s_i$ are known, the object value of $s_i$ is a quadratic and convex function of $(x_i, y_i)$. To calculate the value of $(x_i, y_i)$ that can minimize $obj(s_i)$, the convex optimization is employed by the proposed approach. Based on the convex optimization, the object value can be minimized when the partial derivatives of $x_i$ and $y_i$ are ‘0’, respectively, which is described as follows.

$$
\begin{align*}
\frac{\partial obj(s_i)}{\partial x_i} &= 2x_i \sum_{j=1}^{n} a_{ij} - 2x_i \sum_{j=1}^{n} y_j \cdot a_{ij} = 0 \\
\frac{\partial obj(s_i)}{\partial y_i} &= 2y_i \sum_{j=1}^{n} a_{ij} - 2y_i \sum_{j=1}^{n} x_j \cdot a_{ij} = 0,
\end{align*}
$$

(7)

$$
\begin{align*}
x_i &= \frac{\sum_{j=1}^{n} x_j \cdot a_{ij}}{\sum_{j=1}^{n} a_{ij}} \\
y_i &= \frac{\sum_{j=1}^{n} y_j \cdot a_{ij}}{\sum_{j=1}^{n} a_{ij}},
\end{align*}
$$

(8)

From Equation 8, it can be seen that the adaptive location of $s_i$ is the weighted average location of its information transmission, where the weights are the total amounts of the information transmission between $s_i$ and $s_j$.

C. THE SHRINK PROBLEM OF THE MWSN AND THE COMPENSATION MECHANISM

According to Equation 8, the adaptive location of $s_i$ based on the information transmission records can be found. However, if sensors in a MWSN adapt their locations only according to Equation 8, the shrink problem will occur. The shrink problem means that sensors adapt to concentrate to the center of the MWSN, which will greatly reduce the coverage area (i.e., size) of the MWSN.

The reason for this problem can be explained as follows. An information transmission record (e.g., $itr_{ij}$) can be considered as an adaptive force of $s_i$. The direction of the adaptive force is from the location of $s_i$ to the deployment location of $s_j$ that transmits information with $s_i$ in $itr_{ij}$. The adaptive distance is proportional to the amount of information transmission in $itr_{ij}$ (i.e., $a_{ij}$). If the distribution of neighboring sensors of $s_i$ is balanced, the location adaptation according to Equation 8 does not have the shrink problem. However, if the distribution of all neighboring sensors of $s_i$ biases to one side of $s_i$, which often happens when $s_i$ is on the edge of the MWSN, according to Equation 8, the adaptive location of $s_i$ must bias to the side where its neighboring sensors are located.

As the example shown in FIGURE 3, for a sensor (e.g., $s_1$ in FIGURE 3(a)) in the middle of the MWSN, most of time, the distribution of neighboring sensors of $s_1$ is balanced. While for a sensor (e.g., $s_2$ in FIGURE 3(b)) at the edge of the MWSN, the distribution of neighboring sensors of $s_2$ is more likely to bias to one side of it. After employing Equation 8, $s_2$ will definitely adapt to the side of its neighboring sensors, which reduces the coverage area (i.e., size) of the whole MWSN.

To handle the shrink problem, a compensation mechanism is proposed in this paper. In the compensation mechanism, a hypothetical neighboring sensor (i.e., $h_{s_i}$) is generated for each sensor ($s_i$) in the MWSN, which is to balance the distribution bias of all real neighboring sensors of $s_i$.

To determine the location of $h_{s_i}$, the distribution bias of all real neighboring sensors of $s_i$ should be calculated. For a real neighboring sensor of $s_i$ (e.g., $s_j$), its distribution bias can be considered as a vector $v_{ij}$, where the direction of $v_{ij}$ is from the location of $s_i$ to the location of $s_j$. The length of $v_{ij}$ is the Euclidean distance between $s_i$ and $s_j$. Based on this definition, the vector $v_{ij}$ can be described as follows.

$$
v_{ij} = (x_j - x_i, y_j - y_i),
$$

(9)

where $(x_i, y_i)$ is the current location of $s_i$ and $(x_j, y_j)$ is the location of $s_j$.

According to Equation 9, the distribution bias (i.e., $BV_i = (x_{bv_i}, y_{bv_i})$) of $s_i$ can be calculated based on vectors of all real neighboring sensors of $s_i$ (i.e., $\{v_{i1}, v_{i2}, \ldots, v_{in}\}$) as follows.

$$
\begin{align*}
x_{bv_i} &= \sum_{j=1}^{n} (x_j - x_i) \\
y_{bv_i} &= \sum_{j=1}^{n} (y_j - y_i),
\end{align*}
$$

(10)

where $n$ is the number of real neighboring sensors of $s_i$ (i.e., see Definition 1).
To balance $BV_i$, the vector (i.e., $v_{hs_i}$) of the hypothetical neighboring sensor $hs_i$ should be $v_{hs_i} = (-x_{hs_i}, -y_{hs_i})$. The location of $hs_i$ (i.e., $(x_{hs_i}, y_{hs_i})$) is calculated as follows.

\[
\begin{align*}
    x_{hs} &= x_i + \sum_{j=1}^{n} (x_i - x_j) \\
    y_{hs} &= y_i + \sum_{j=1}^{n} (y_i - y_j),
\end{align*}
\]  

(11)

Except for the location of $hs_i$, the amount of information (i.e., $a_i(hs_i)$) that is transmitted between $s_i$ and $hs_i$ should also be generated. In the proposed compensation mechanism, the amount of information that is transmitted between $s_i$ and $hs_i$ is proportional to the average amount of information that is transmitted between $s_i$ and all its neighboring sensors, which can be calculated as follows.

\[
a_{hs_i} = \frac{\beta \sum_{j=1}^{n} a_{ij}}{n},
\]  

(12)

where $\beta$ is the compensation coefficient to control the amount of compensation, $n$ is the number of neighboring sensors of $s_i$ and $a_{ij}$ is the amount of information that is transmitted between $s_i$ and its $j^{th}$ neighboring sensor $s_j$.

Based on all above equations, the final adaptive location (i.e., $(adx_i, ady_i)$) of the sensor $s_i$ based on its information transmission records and the hypothetical neighboring sensor $hs_i$ can be calculated as follows.

\[
\begin{align*}
    adx_i &= \frac{\beta \sum_{j=1}^{n} a_{ij} + \sum_{j=1}^{n} x_j \cdot a_{ij}}{\beta \sum_{j=1}^{n} a_{ij} + \sum_{j=1}^{n} a_{ij}} \\
    ady_i &= \frac{\beta \sum_{j=1}^{n} a_{ij} + \sum_{j=1}^{n} y_j \cdot a_{ij}}{\beta \sum_{j=1}^{n} a_{ij} + \sum_{j=1}^{n} a_{ij}},
\end{align*}
\]  

(13)

D. THE LOCATION ADAPTATION OF SENSORS IN REAL MWSN APPLICATIONS

Based on Equation 13, sensors in a MWSN can find their optimal adaptive location for the efficient information transmission. However, in real applications, there are two problems that need to be solved during the location adaption of sensors in a MWSN, which are described as follows.

1) Since the adaptive location of a sensor is calculated from the current locations of its neighboring sensors, each sensor and its neighboring sensors in the MWSN cannot adapt their locations at the same time;

2) Since the location adaption of sensors is based on the information transmission regularity of sensors in the MWSN, if sensors in a MWSN have no information transmission regularity, it will lead sensors in the MWSN to frequently adapt their locations.

To solve the first problem, we propose a token-based outside-in sensor adaption mechanism. The reason to use the outside-in adaption mechanism is that the location adaption of peripheral sensors can ensure the coverage area (i.e., size) of the MWSN. Specifically, the proposed mechanism is described as follows.

1) Before the location adaption, each peripheral sensor in the MWSN generates a token;
2) The sensors that have tokens begin to adapt their locations in turn;
3) After the location adaption, the sensors pass the tokens to their non-token neighboring sensors;
4) Repeating steps 2) and 3) until all sensors in the MWSN adapt their deployment locations.

The proposed mechanism can prevent the problem that a sensor and its neighboring sensors adapt their location at the same time.

For the second problem, our solution is through adding the adaptive threshold for the location adaption of sensors. The influence of the adaptive threshold can be described as follows. After calculating the adaptive location through Equation 13, the adaptive distance (i.e., $d$) of the sensor is calculated from the deployment locations of the sensor before and after the location adaption. If the adaptive distance is less than the adaptive threshold (i.e., $d < \text{Threshold}$), then we think that the adaptive distance of the sensor is too small to have a great impact on the energy consumption of its information transmission, so the location adaption is abandoned. On the contrary, if the adaptive distance is more than or equal to the adaptive threshold (i.e., $d \geq \text{Threshold}$), we believe that the location adaption of the sensor is very important and can effectively reduce the energy consumption of its information transmission, so the location adaption should be conducted. By adjusting the value of the adaptive threshold, the frequency of location adaption of sensors in a MWSN can be controlled and reduced.

IV. EXPERIMENTS

In this section, first, the experiment is conducted to evaluate the performance of the proposed approach (i.e., the optimization method and the compensation mechanism) to reduce the energy consumption for the information transmission of sensors in a MWSN. In addition, the performance of the compensation mechanism to avoid the shrine problem is also evaluated. Finally, we evaluate the influence of the adaptive threshold on the location adaption of sensors. At present, there is few mobile wireless sensor adaption approaches for the efficient energy management. So, in the experiment, we mainly use the quantitative method to evaluate the performance of our approach.

A. EXPERIMENTAL SETTINGS

The experiments are performed on a PC with 2.6 GHz Intel Core i7 processor, and 8 GB memory. We use Matlab R2018b to simulate the experimental environment. In the experiments, 30 wireless mobile sensors are randomly deployed to form a MWSN in a 30 x 30 environment. The total amount of information that is transmitted between two sensors is between
1000 bytes to 10000 bytes. The compensation coefficient $\beta$, which represents the compensation of hypothetical sensors on the location adaption of sensors, is ranged from 0 to 1 with 0.2 per step. During the experiment, we found that when the threshold is more than 5 units of distance, all sensors in the MWSN do not move. Therefore, the adaptive threshold for the location adaption of sensors is ranged from 0 to 5 units of distance with 0.2 per step.

The settings of experiments are shown in Table 1.

| Name                              | Value                      |
|-----------------------------------|----------------------------|
| The size of the environment       | $30 \times 30$ (unit of distance) |
| The number of sensors             | 30                         |
| The amount of information transmission | 1000 $\sim$ 10000 bytes   |
| The compensation coefficient $\beta$ | 0 $\sim$ 1 with 0.2 per step |
| The adaptive threshold $Threshold$ | 0 $\sim$ 5 with 0.2 per step |

To evaluate the performance of the proposed approach, three parameters of a MWSN are calculated and compared in the experiment, which are the object value (i.e., $obj(S)$), the size (i.e., $cov(S)$) and the number of location adaption of sensors in the MWSN (i.e., $num(S)$).

The object value of the MWSN $obj(S)$ represents the energy consumption for the information transmission of sensors in the MWSN, which is derived from [11] (i.e., The energy consumption for the information transmission of wireless sensors is proportional to the square of the information transmission distance) and calculated based on Equation 3.

The size of the MWSN $cov(S)$ reflects whether the compensation mechanism avoid the shrink problem of the MWSN after the location adaption of sensors, which can be calculated as follows.

$$cov(S) = (\max(x_{i1}) - \min(x_{i1})) \times (\max(y_{i3}) - \min(y_{i4})), \quad (14)$$

where $\max(x_{i1})$ and $\min(x_{i1})$ are the maximum and minimum values of x-coordinate of sensor locations in the MWSN, respectively. While $\max(y_{i3})$ and $\min(y_{i4})$ are the maximum and minimum values of y-coordinate of sensor locations in the MWSN, respectively.

### B. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results are shown in FIGURE 4, 5 and 6.

In FIGURE 4, the X-axis is the values of $\beta$, while the Y-axis is the object values (i.e., $obj(S)$) of the MWSN. From FIGURE 4, it can be seen that when $\beta$ is 0 (i.e., there is no compensation to balance the distribution bias of sensors), after employed the proposed approach to adapt the sensors’ locations, the object value $obj(S)$ of the MWSN can be greatly reduced (from 58819.3 to 32213.3, around 54.8%). With the increase of $\beta$, after the location adaption of sensors, the reduction of $obj(S)$ is becoming smaller and smaller. This is because that the compensation of hypothetical sensors prevents the sensors in the MWSN to achieve their objects. Therefore, when $\beta$ is 1 (i.e., the compensation is dominant the location adaption of sensors), after the location adaption of sensors, $obj(S)$ is even more than $obj(S)$ before the location adaption of sensors, which means that after location adaption, sensors consume more energy for the information transmission. According to the experiment, it can be seen that the
suitable value of $\beta$ is important for the performance of the proposed approach.

In FIGURE 5, the X-axis is the values of the compensation coefficient $\beta$, while the Y-axis is the sizes (i.e., $cov(S)$) of the MWSN. From FIGURE 5, it can be seen that when $\beta$ is 0 (i.e., there is no compensation to balance the distribution bias of sensors), after employed the proposed approach to adapt the sensors’ locations, the size $cov(S)$ of the MWSN is greatly reduced (from 841 to 509.1, around 39.5%), which means that after the location adaption, a very serious shrink problem occurs in the MWSN. It can be seen that the optimization method of the proposed approach leads to the shrink problem in the MWSN during the location adaption of sensors. With the increase of $\beta$, after the location adaption of sensors, the shrink problem of the MWSN is alleviated. This is because that the compensation mechanism of the proposed approach prevents the shrink of the MWSN during the location adaption of sensors. Therefore, when $\beta$ is 1 (i.e., the compensation is dominant the location adaption of sensors), after the location adaption of sensors, $cov(S)$ is even larger. This experiment indicates that the compensation mechanism can effectively prevent the shrink problem of the MWSN during the location adaption of sensors.

In FIGURE 6, the X-axis is the values of the adaptive threshold, the Y-axis (on the left) is the number $num(S)$ of location adaption of sensors in the MWSN and the Y-axis (on the right) is the object value $obj(S)$ of the MWSN after the location adaption of sensors. From FIGURE 6, it can be seen when the adaptive threshold is 0 (i.e., the sensors always adapt their locations based on the information transmission regularity), after employed the proposed approach to adapt the sensors’ locations, the number of location adaption of sensors $num(S)$ in the MWSN is 30, which means that all 30 sensors in the MWSN have adapted their locations. With the increase of the adaptive threshold, the number of location adaption of sensors decreases, when the threshold is 4.8, the number of location adaption of sensors in the MWSN is 0, which means that there is no sensor in the MWSN adapting their deployment locations, since all their adaptive distances are less than the adaptive threshold.

Comparing with the number $num(S)$ of location adaption of sensors, the object value of the MWSN after the location adaption of sensors shows an opposite tendency. When the adaptive threshold is 0, since all sensors in the MWSN can adapt their locations according to the latest information transmission regularity, after the location adaption, the energy consumption for the information transmission (i.e., the object value $obj(S)$) of the MWSN can be reduced to the lowest level (131535.7). With the increase of the adaptive threshold, since the number of sensors that adapt their deployment locations decreases, $obj(S)$ of the MWSN after the location adaption increases. When the threshold is 4.8, since no sensor in the MWSN adapts the deployment location, the energy consumption for the information transmission in the MWSN has no changes and is still 251766.2 after the location adaption. Therefore, when using the proposed approach, we should choose the appropriate adaptive threshold, so as to reduce the number of location adaption of sensors as well as the energy consumption of sensors in the MWSN.

In summary, from the experiment, it can be seen that the optimal method of the proposed approach can effectively reduce the energy consumption for the information transmission of sensors in a MWSN. However, our optimal method also brings the shrink problem to the MWSN after the location adaption of sensors. Therefore, a compensation mechanism is proposed to handle the shrink problem of the MWSN. To improve the adaptability of the compensation mechanism, the compensation coefficient $\beta$ is add to adjust the compensation strength. From the experiment, it can be seen that the value of $\beta$ plays an important role in the MWSN after the location adaption of sensors. The big $\beta$ value (i.e., close to 1) increases the energy consumption of sensors and the coverage area (i.e., $cov(S)$) of the MWSN. If the value of $\beta$ is too small (i.e., close to 0), although the optimal method can greatly reduce the energy consumption for the information transmission of sensors, the work efficiency of the MWSN will be greatly reduced due to the coverage area reduction of the MWSN. Through a large amount of experiments, we believe that the suitable value of $\beta$ is between 0.4 and 0.5, depending on the application scenario.

In addition, if there is no information transmission regularity in the MWSN, in order to avoid the frequent location adaption of sensors in the MWSN, the adaptive threshold is proposed. If the adaptive distance of sensors is less than the adaptive threshold, we think that the current sensor adaption will not have a great impact on the energy consumption of the sensor and the coverage area of the MWSN. We abandoned the current sensor adaption and adapt the locations of sensors with greater impacts. For our experimental settings, we think the appropriate adaptive threshold is 1.2. The same as $\beta$, the appropriate adaptive threshold depends on the application scenario.

V. THE RELATED WORK

In the last twenty years, many approaches are proposed for sensors to reduce their energy consumption and extend their lifetime from different perspectives [1], [8]–[10], [19]–[21].

Yang et al. [18] proposed a relay placement approach for sensor networks [18], which considers the two important issues in long-term sensor networks: the energy and the connectivity. In their approach, the deployment locations of relays are found through a tradeoff between the longest lifetime of relays and the maximum coverage of sensors.

Rogers et al. [11] proposed a self-organized approach to adapt the information transmission routing of sensors in wireless micro-sensor networks. In their approach, to reduce the energy consumption for the information transmission, Rogers et al. enable sensors in a WSN to adapt their information transmission routing, which transmit information with the assistant of neighboring sensors. By doing so, sensors can greatly reduce their information transmission distances so as
to reduce the energy consumption for the information transmission. However, most of these approaches are proposed for static WSNs, where the sensor cannot move. Different with these approaches, the proposed approach aims to use the mobility of the mobile wireless sensors to reduce the energy consumption through adapting their locations to reduce the information transmission distances with neighboring sensors.

Heo and Varshney [6] proposed a self-spreading approach for the location adaption of mobile wireless sensors which was inspired by the equilibrium of molecules. The strength of the interaction force between two mobile wireless sensors is calculated from the distance between the two sensors. The final location of each sensor is the balance point of interaction forces. Through controlling the strength of interaction forces, Heo et al.’s approach can adapt the distances between sensors. However, based on their approach, the distances between a sensor and its neighboring sensors are always the same. Different from Heo et al.’s approach, the proposed approach adapts the locations of sensors according to the information transmission regularity in the MWSN, which is more suitable to reduce the energy consumption for the information transmission than the molecule equilibrium-based approach.

Currently, although many approaches to reduce the energy consumption of sensors have been proposed for WSN, most of them are proposed for the static WSN, where sensors cannot move. For the MWSN, as far as we know, most of researches mainly focus on the use of sensors’ mobility to achieve routine or self-organization. Although the work of Heo et al. uses the mobility of sensors to improve the work efficiency and effectiveness of the MWSN, the aim of their works is to increase the coverage area of the established MWSN, rather than reduce the energy consumption of sensors. Therefore, the proposed approach is innovative and has academic and practical values.

VI. CONCLUSION

In this paper, a decentralized self-adaptive approach is proposed for sensors in a MWSN to adapt their locations so as to reduce their energy consumption for the information transmission. To achieve this object, an optimization method is proposed to adapt sensors’ locations according to their information transmission regularity. In addition, to handle the shrink problem of the MWSN during the sensor location adaption, a compensation mechanism is proposed, which generates hypothetical sensors to balance the distribution bias of real neighboring sensors. Finally, the token-based mechanism and the adaptive threshold are introduced to enable sensors in real MWSN to achieve the efficient location adaption. The experimental results have shown that through the proposed approach (i.e., the optimization method and the compensation mechanism), the energy consumption for the information transmission of sensors in a MWSN can be effectively reduced. In the future, we will improve the compensation mechanism of the proposed approach. Currently, for all sensors in the MWSN, the compensation coefficients ($\beta$) are the same. We would like to set private $\beta$ for each sensor, so as to make it to accurately compensate distribution bias of neighboring sensors.

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XING SU received the B.Sc. degree from the School of Software Engineering, Beijing University of Technology, Beijing, China, in 2007, and the M.Sc. and Ph.D. degrees in computer science from the University of Wollongong, Australia, in 2012 and 2015, respectively. He is currently a Lecturer with the Faculty of Informatics, Beijing University of Technology. His research interests include distributed artificial intelligence, multiagent systems, disaster management, and service-oriented computing.

ZHI CAI received the M.Sc. degree from the School of Computer Science, The University of Manchester, in 2007, and the Ph.D. degree from the Department of Computing and Mathematics, Manchester Metropolitan University, U.K., in 2011. He is currently an Associate Professor with the College of Computer Science, Beijing University of Technology, China. His research interests include information retrieval, ranking in relational databases, keyword search, and intelligent transportation systems.

XIBIN JIA received the B.S. degree in wireless technology from Chongqing University, in 1991, the M.S. degree in intelligent instrument from the North China Institute of Science and Technology, in 1996, and the Ph.D. degree in computer science and technology from the Beijing University of Technology, Beijing, China, in 2007. She is currently a Professor with the College of Computing, Beijing University of Technology. Her current areas of interest include intelligent information cognition and computing.

LIMIN GUO received the bachelor’s degree from the Huazhong University of Science and Technology, in 2005, and the Ph.D. degree from the Institute of Software, Chinese Academy of Sciences, in 2012. She is currently a Lecturer with the Beijing University of Technology. Her research interests include database research and implementation, spatial-temporal data mining, and so on.

ZHIMING DING received the bachelor’s degree from Wuhan University, in 1989, the master’s degree from the Beijing University of Technology, China, in 1996, and the Ph.D. degree from the Institute of Computing Technology, Chinese Academy of Sciences, in 2002. He is currently a Professor with the College of Computer Science, Beijing University of Technology. He owns five invention patents and has published three books and about 120 articles in academic journals and conferences. His main research interests include database systems, mobile and spatial-temporal data management, intelligent transportation systems, sensor data management, and information retrieval.