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Efficient Energy Management to Prolong Lifetime of Wireless Sensor Network

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1. Introduction

Since the batteries in a wireless sensor network are either hard to charged or replaced, how to efficiently utilize limited energy in a wireless sensor network has become an important issue. Those operations for a sensor to consume energy are target detection, data transmission and reception, data processing, etc. Among others data transmission consumes most of the energy, and it heavily depends on the transmission distance and the transmitted data amount. In the literature those methods have been devoted to energy saving problems can be categorized into shortening transmission distance (Heinzelman et al., 2000), reducing transmitted data amount (Klein, 1993), scheduling radio transceivers (Busse et al., 2006), scheduling sensing components (Huang & Tseng, 2003), adjusting transmission range (Wang, 2004), and adjusting detection range (Cardei et al., 2006). Our approach focuses on adjusting the detection range of each sensor in order to reduce the overlaps among detection ranges while keep the detection ability above a predefined threshold. If we can largely reduce the overlaps among detection ranges and effectively decrease the amount of duplicate data then we will be able to save energy more efficiently. Meguerdichian et al. (2001) exploited the coverage problem in wireless ad-hoc sensor networks in terms of Voronoi diagram and Delaunay triangulation. In this paper we propose a Voronoi dEtection Range Adjustment (VERA) method that utilizes distributed Voronoi diagram to delimit the responsible detection range of each sensor. Then we use Genetic Algorithm to optimize the most suitable detection range of each sensor. Simulations show that VERA outperforms Maximum Detection Range, *K*-covered (Huang & Tseng, 2003), and Greedy (Cardei et al., 2006) methods in reducing the overlaps among detection ranges, minimizing energy consumption, and prolonging network lifetime.

This paper is organized as follows. Section 2 has a detailed survey on the related work. Section 3 introduces a five-step framework of our proposed methodology, which includes position determination, detection range partition, grid structure establishment, detection power minimization, and detection power adjustment. Section 4 presents system simulations and results. Finally, section 5 offers brief concluding remarks.

2. Related work

In a wireless sensor network, wireless transmission consists of three major operations: (1) convert data into radio waves, (2) amplify radio waves until reaching the receiving sensors, (3) receiving sensors receive data. The amount of energy consumed in each of the three operations is proportional to the transmitted data amount. Furthermore, the amount of energy consumed in operation (2) is inversely proportional to the square of the distance between two communicating sensors. Both of them imply energy consumption can be effectively reduced by shortening the transmission distance and reducing the transmitted data amount.

Much research has been devoted to energy saving problem in the literature. Those approaches can be classified into shortening transmission distance, reducing transmitted data amount, scheduling radio transceivers, scheduling sensing components, adjusting transmission range and adjusting detection range.

Heinzelman's work (Heinzelman et al., 2000) focuses on shortening the transmission distance in order to reduce energy consumption. Given that sensor A has data to be forwarded to sensor C, if there exists a sensor B such that $[dist(A,C)]^2 \geq [dist(A,B)]^2 + [dist(B,C)]^2$ then the original routing path "sensor A $\rightarrow$ sensor C" will be changed to "sensor A $\rightarrow$ sensor B $\rightarrow$ sensor C". Klein's work (Klein, 1993) is based on data fusion. Klein assumed the data collected by those sensors within the same area should be quite similar (redundant). For example, the collected temperatures from sensors of the same area are about the same. Once all these similar data forwarded to a responding sensor, it fuses these data before forwarding to the next stop. This may thus mitigate energy consumption by reducing transmitted data amount. Data fusion usually works with clustering. Sensors in a clustering structure are classified into different clusters according to their locations. Each cluster has a cluster head that is responsible for collecting, fusing and forwarding data. Due to overloaded workload of cluster head, it usually consumes the most energy than the other cluster members. To prolong the lifetime of the whole sensor network, all cluster members should take turns to serve as the cluster head. Energy saving can also be achieved through scheduling. Sensor is made of different components, e.g., sensing component, processor, transceiver, memory and battery. Each component can be individually enabled to operation. Those components of a sensor that are not in operations can be turned off temporarily for the sake of energy saving. This can be realized through scheduling of radio transceivers and sensing components. Scheduling of radio transceivers means to turn the transceivers on (operating mode) and off (sleep mode). Those transceivers that are not responsible for transmitting and relaying data could be turned off while other components, like sensing components and processors, function normally. Busse et al. (2006) proposed a Topology and Energy Control Algorithm (TECA). In TECA, each sensor in a cluster, after functioning for a while, has to determine whether it should turn off its transceiver or not. This decision is made according to the role it plays in the cluster. If a sensor serves as a cluster head or bridge (the one connecting nodes between two clusters) then it keeps, otherwise, turns it off. Even if a sensor moves to sleep mode, it still listens to the messages from the cluster. Once, a sensor is called to serve as a cluster head (or bridge), it resumes itself from sleep mode and turns on its transceiver. Sensing components can be scheduled in a similar way. A sensor turns off those sensing components that are not on duty. Such sensor can still transmit and forward data. Huang & Tseng (2003) proposed a *K*-covered method that is able to cover a sensor field in a 2D or 3D space with least number of sensors. With scheduling, it may come

to another energy saving problem. Each component of a sensor may be turned on and off frequently. Restarting sensor components from sleep mode frequently may consume more energy than that saved by staying in sleep mode. Some researchers proposed adjusting the communication range of each sensor to just enough short distance. This adjustment is usually based on optimization. Wang (2004) proposed adjusting the transmission power of each sensor in order to reduce the communication range of each sensor and thus save much energy. His method should work under the precondition of no broken connections. Detection range adjustment is an alternative approach without extra power consumption due to restarting sensors. In the recent years active sensors, like microwave sensors, are able to proactively detect moving objects by using microwave, laser, ultrasonic, etc. This also makes energy saving possible by simply adjusting sensing power and detection range. Cardei et al. (2006) proposed a Greedy algorithm to solve target coverage problem by adjusting detection range. Area coverage problem means how to use limited sensors to cover the whole area, while target coverage problem considers only how to cover all targets in that area. Cardei et al., first, randomly deployed several targets in a sensing field, then generated set covers to fully cover those targets. Each set cover is formed by several sensors, and each sensor is allowed to join different set covers. All these set covers are then used to monitor all targets in turn.

3. Methodology

We assume that there are n sensors, $S_1, S_2, \ldots, S_n$, randomly deployed to cover a detection field, F. Each sensor is able to adjust its detection power, K_i, and connect to all those neighbours within its transmission range. The detection power corresponds to a detection range, D_i. The detection ability of each sensor must be greater than a threshold, α ($0 < \alpha < 1$). The aim of this research is to minimize the overlaps of detection ranges in order to minimize the total detection power, ΣK_i, of the whole network.

The proposed methodology can be divided into five steps. The first step is position determination, which is used to determine the position of each sensor. The second step is detection range partition, where each sensor uses Voronoi diagram algorithm to delimit its responsible detection range. The third step is grid structure establishment, where each grid point corresponding to an area is used to calculate the detection probability of that area. The fourth step is detection (sensing) power minimization, where we use Genetic Algorithm to minimize the total detection power of the whole network. The final step is detection (sensing) power adjustment. This adjustment is based on the results of detection power minimization. Fig. 1 shows the framework of the five-step methodology.
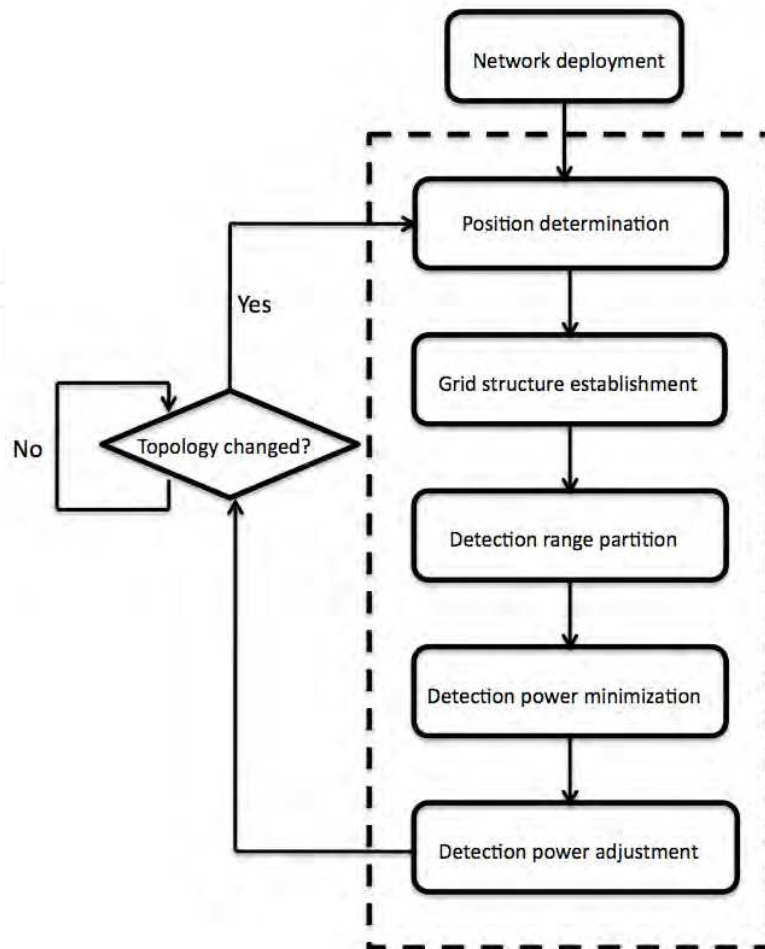
Fig. 1. Framework of the five-step methodology

Before proposing the framework of five-step methodology, we introduce some useful formulae.

3.1 Related formulae

Free space loss of radio wave

$$\text{Free space loss} = 20\log\frac{4\pi d}{\lambda} \tag{1}$$

Where λ is the wavelength and d is the transmitted distance. Free space loss is the attenuation rate of a transmitted radio wave.

Detection power, E_i, of sensor S_i to a target

$$\text{Pr} = Pt + Gain - 20\log\frac{8\pi d}{\lambda} \tag{2}$$

Where Pt is the emitted detection power of a sensor, $Gain$ is antenna gain, d is the distance between sensor and target, and Pr is the radio power received by the sensor from a target.

In a wireless sensor network, a detection process consists of a sensor transmitting a detection radio wave and receiving bounced back radio wave. A larger Pr indicates higher detection ability of a sensor to a target. In addition to Pr, the detection energy of sensor S_i to a target also includes the thermal noise, N_i, generated by electronic component of sensor S_i. Thus the total detection energy, E_i, to a target is the sum of Pr and N_i.

$$E_i = \mathrm{Pr} + N_i \qquad (3)$$

Detection probability, $P_i(u)$, of a node at position u by sensor S_i

$$P_i(u) = prob[E_i(u) > \beta] = prob[\mathrm{Pr}(u) + N_i > \beta] \qquad (4)$$

$P_i(u)$ is the detection probability that an event occurs at position u detected by sensor S_i. β is a threshold used to determine whether an event is triggered. As the detected energy is larger than β, a corresponding event is triggered. Otherwise, the detected energy is thought to be a thermal noise.

Conjunctive detection probability

$$P(u) = 1 - [\prod (1 - P_i(u))] \qquad (5)$$

On the other hand, a position u might be covered by more than one detection range of different sensors. Let an event occur at a position, u, the probability that all sensors do not detect is $\prod (1 - P_i(u))$. Therefore, the conjunctive detection probability, $P(u)$, of all sensors is $1 - [\prod (1 - P_i(u))]$.

With all the related formulae, we introduce each step of the proposed methodology in the following subsections.

3.2 Position determination

The first step is to determine the position of each sensor. If each sensor is equipped with a GPS, the system could have the absolute position of each sensor. However, this kind of sensors will be limited to being placed in an outdoor environment. Besides, it makes sensor bigger and consumes more energy. In the proposed method, we consider the position of each sensor in terms of relative position. These positions can be calculated by either one of AOA (Angle of Arrival), TDOA (Time Difference of Arrival) and RSSI (Received Signal Strength Indicator) methods. If each sensor knows only the relative positions between itself and its neighbours, it will not be able to compute the Voronoi diagram of the whole network. On the other hand, if all sensors send their positions to base stations, it will consume huge bandwidth and transmission energy. This problem will be solved by improving the Voronoi diagram in the following subsection.

3.3 Detection range partition

After position determination, each sensor will be able to know the relative positions of its 1-hop neighbours. The next step is to determine the responsible detection range of each sensor. Meguerdichian et al. (2001) exploited the coverage problem in wireless ad-hoc sensor networks in terms of Voronoi diagram and Delaunay triangulation. In this research,

we employ Voronoi diagram to delimit the responsible detection range of each sensor. Voronoi diagram can be used to divide an area into sub-areas. In a Voronoi diagram, it holds the property that the nearest site of any point x in a sub-area $V(P_i)$ must be P_i (site).

Definition : *Voronoi diagram*

Let $P = \{P_1, P_2,...,P_n\}$, $n \geqq 2$, P is a set of nodes in an area, and $P_1, P_2, ..., P_n$ are sites.

$V(P_i) = \{x: P_i\text{-}x \leqq P_j\text{-}x, \ \forall j \neq i\}$

$V(P) = \{V(P_1), V(P_2),......, V(P_n)\}$

$V(P)$ is called a Voronoi diagram.

Fig. 2. shows the Voronoi diagram formed by three sites P_1, P_2, P_3. The nearest site of a random point x in the sub-region $V(P_1)$ must be P_1. The same principle applies to both $V(P_2)$ and $V(P_3)$. Fig. 3 shows the sub-regions of random deployed sensors using Voronoi diagram.
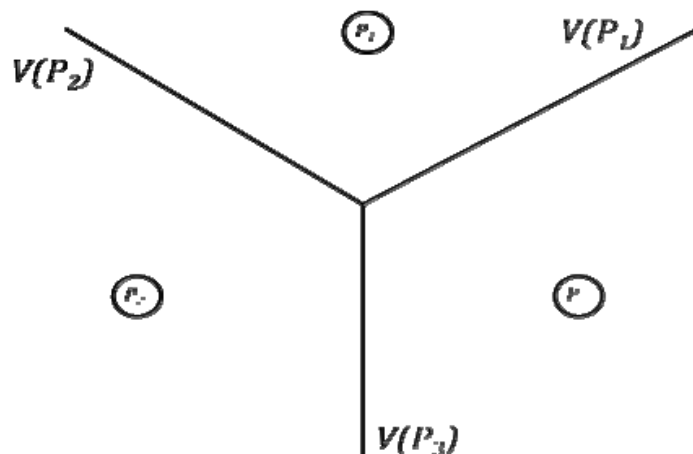
Fig. 2. The Voronoi diagram formed by three sites (P_1, P_2, P_3)
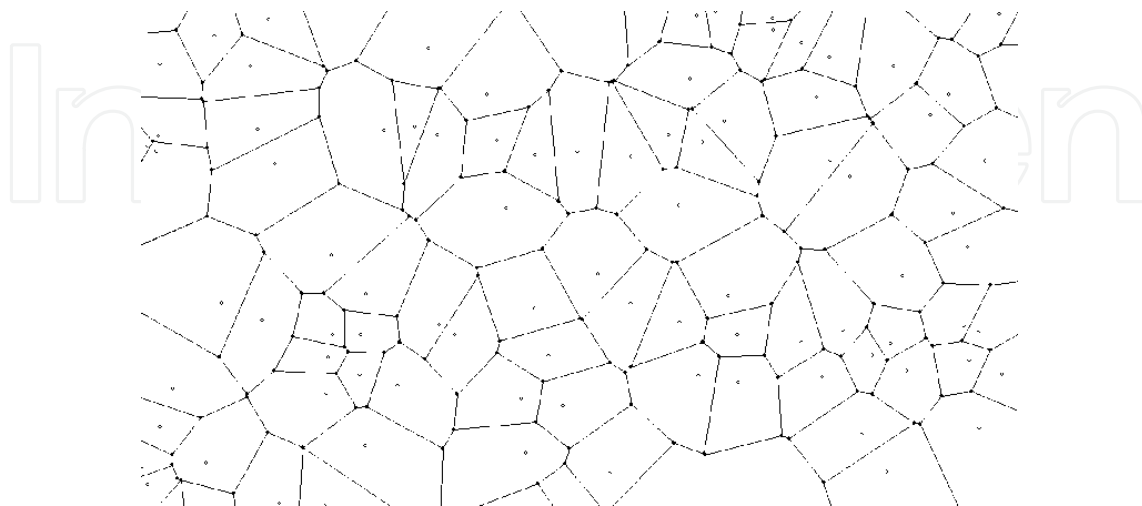
Fig. 3. Sub-regions of random deployed sensors using Voronoi diagram

Next, we determine the responsible detection range of each sensor. Fig. 4 shows part of the Voronoi diagram formed by sensor A and its neighbours, where the quadrangle is the sub-region of sensor A. Fig. 5 shows the case when the responsible detection range covers the sub-region of sensor A. Fig. 6 shows another case when the detection range does not fully cover the sub-region of sensor A due to its limited sensing power. In such case the responsible detection range is equal to its maximum detection range.
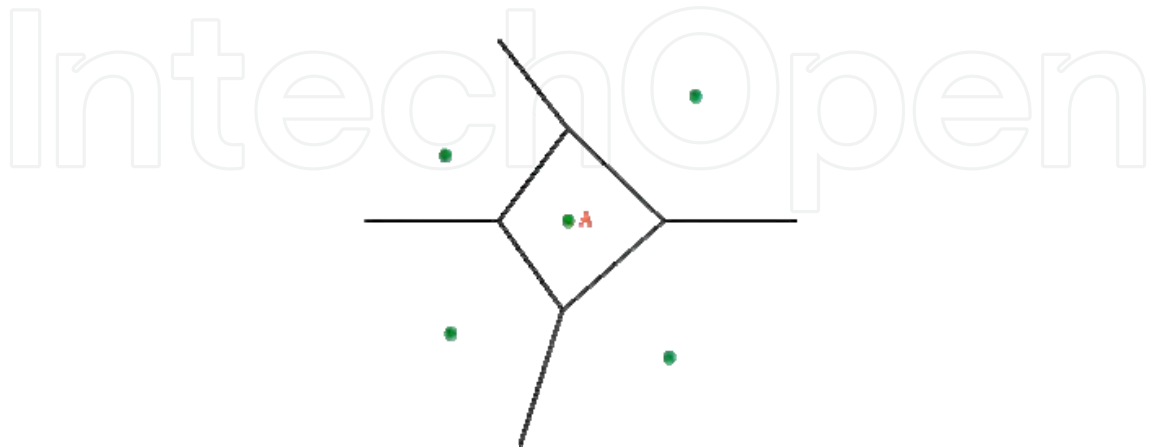
Fig. 4. Sub-regions formed by sensor A and its neighbours
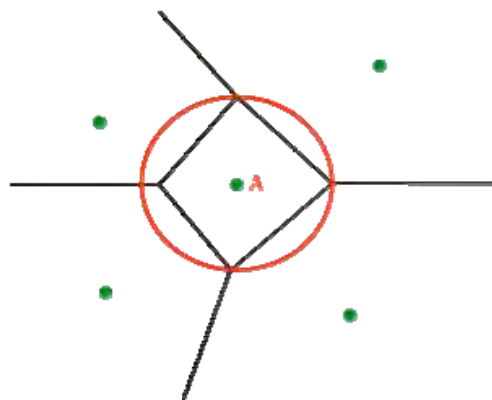
Fig. 5. The responsible detection range covers the sub-region of sensor A
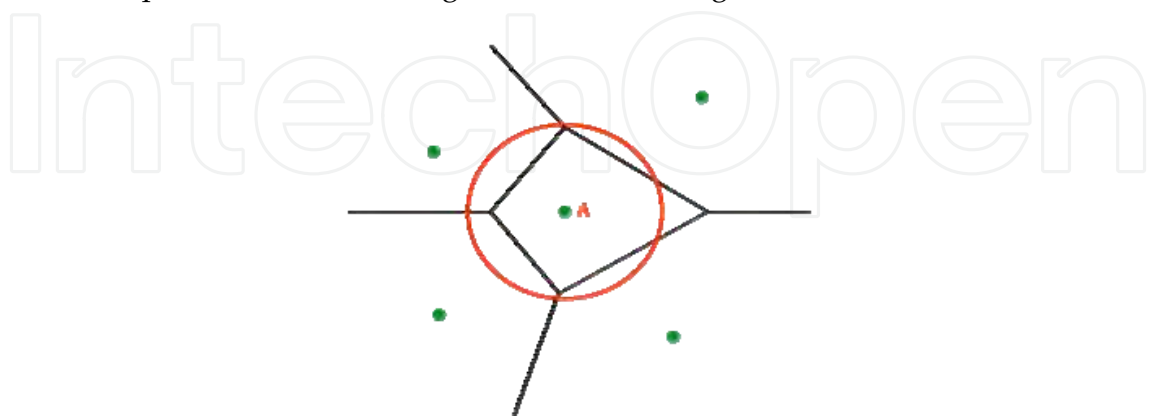
Fig. 6. The sub-region of sensor A is larger than its maximum detection range

Besides, it can be proved that if the maximum transmission distance between two sensors is greater than twice the maximum detection range of each sensor then the responsible

detection ranges of the two sensors do not overlap. Fig. 7 shows that sensor A and B are not neighbours to each other. Though their sub-regions are overlapped, their responsible detection ranges do not overlap.
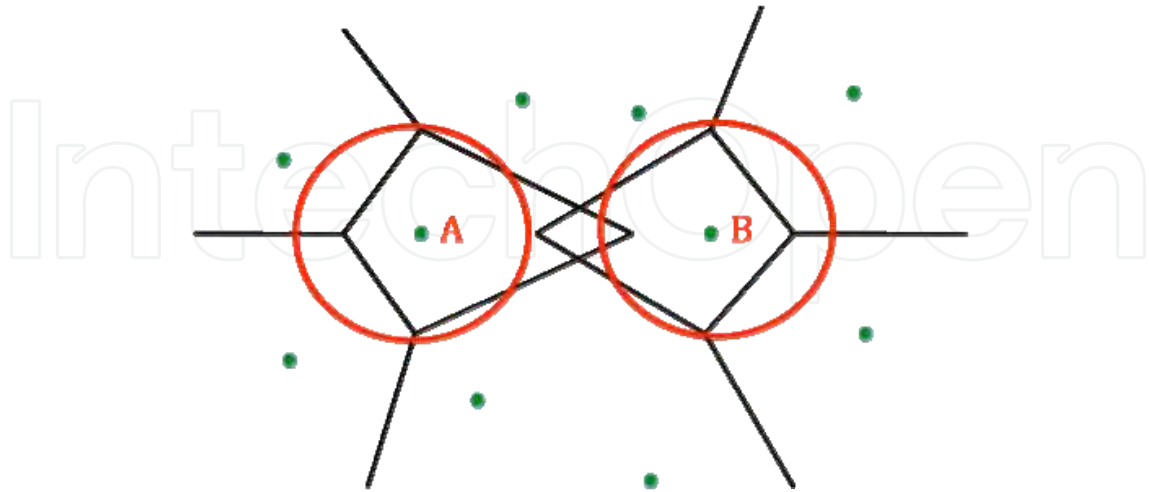
Fig. 7. The sub-regions of sensors A and B overlap, but their responsible detection ranges do not overlap

3.4 Grid structure establishment

To make sure that the detection ability of each sensor is greater than a predefined threshold, α, we create a grid structure for detection field, F. In a grid structure, each grid point represents a target. In Fig. 8, the solid circles are sensors and each vertex of a square is a grid point.
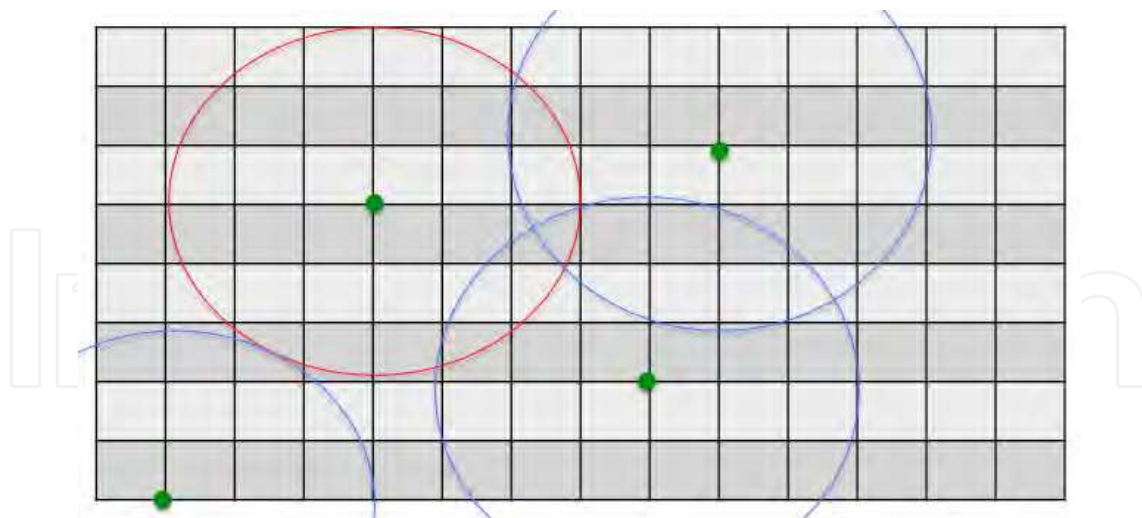
Fig. 8. Grid structure of a target detection area

Assume that there are m grid points in the responsible detection range of sensor S_i. Let $P(u)$ be the conjunctive detection probability, Γ be the threshold of detection probability of the grid point u. We define G_i to be the set of those u whose $P(u)$ is smaller than Γ, that is $G_i = \{u \mid u \in S_i, P(u) \leq \Gamma\}$. We also define $1 - \dfrac{|G_i|}{m}$ to be the detection ability of sensor S_i.

The greater $1 - \frac{|G_i|}{m}$, the higher detection ability of sensor S_i. In addition, we set another threshold, α, for S_i. While reducing the overlaps of detection ranges, the system should keep the detection ability above the threshold α.

Fig. 9 shows the detection ability of sensor S_i. There are 29 grid points spread in distinct locations. We assume the threshold of the detection ability, Γ, is 0.7. Since the detection abilities of the grid points A, B, C, D and E are less then 0.7, all these five points belong to set G_i. We can thus compute the detection ability of S_i, $1 - \frac{|G_i|}{m}$, is 24/29.
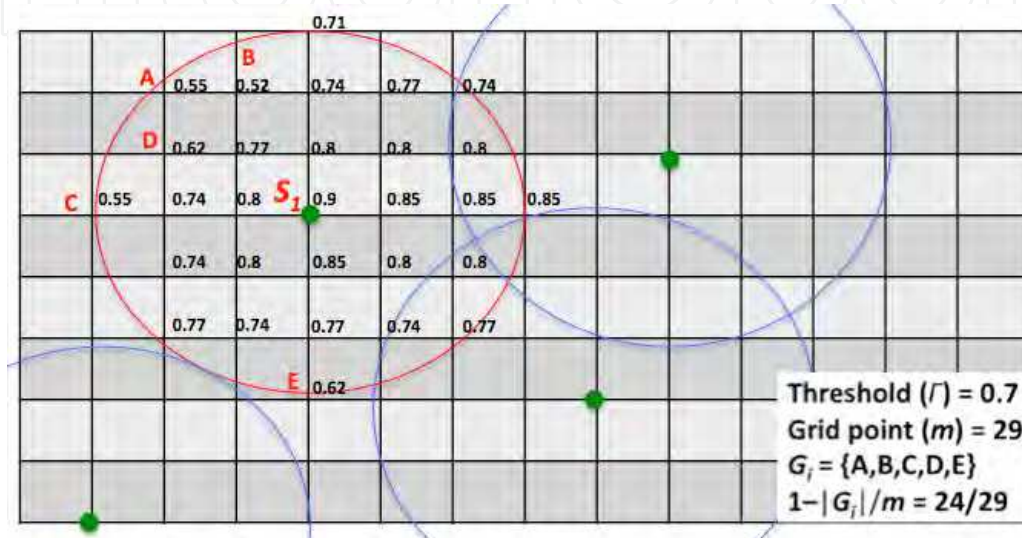
Fig. 9. Detection ability of sensor S_i

3.5 Detection power minimization

After establishing the grid structure, our goal is to minimize the detection power, K_i, or equivalently the, P_t. We use a Genetic Algorithm (GA) to do the minimization. GAs are the methods used to find exact or approximate solutions to optimization and search problems. GAs are often used to solve those problems of high-complexity, like NP-problem, in limited time. Fig. 10 shows the operation flow of genetic algorithms.

Chromosome encoding: encode species into chromosome string according to the attributes of the problem domain. Each chromosome string is thought of as a problem solution.

Objective function: used to evaluate a chromosome string, determine the adaptation degree (fitness) of a chromosome string. In general, the higher adaptation degree of a chromosome string, the better solution.

Selection: select highly evaluated chromosome strings as parents of offersprings. A highly evaluated chromosome string usually has higher probability being selected.

Genetic operations: can be either Crossover or Mutation. Crossover is used to produce better chromosome strings (offsprings) by exchanging sub-strings of parents. Mutation is different from crossover in that it changes (e.g., 0→1, 1→0) very few codes of parents to escape from local optimum. Mutation occurs much less frequent than crossover does.

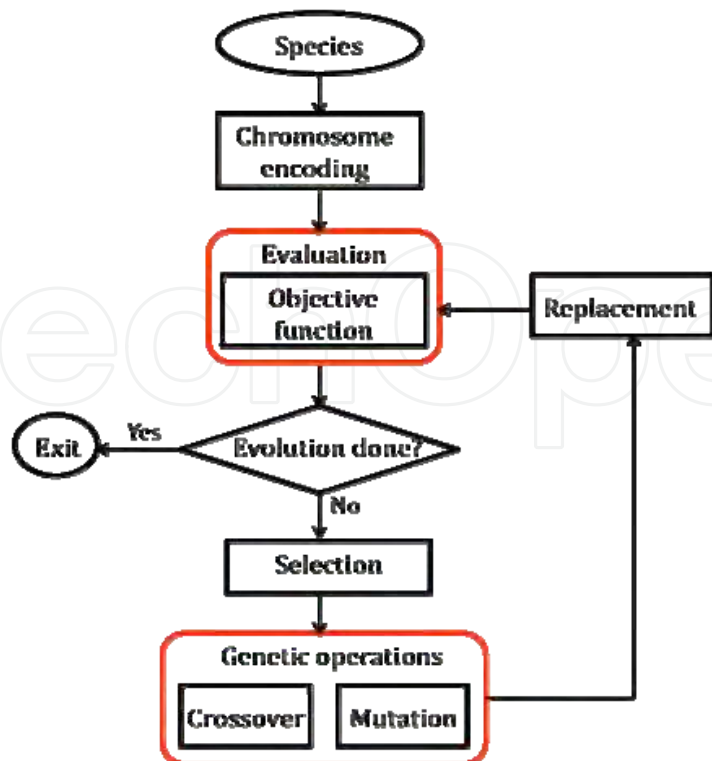*Replacement*: replace old chromosome strings (parents) by new chromosome strings (offsprings).

Fig. 10. Operation flow of genetic algorithms.

Chromosome encoding

First, we encode the detection powers of sensors, $S_1, S_2,…,S_n$, into a chromosome string, $K_1,K_2,…,K_n$. Then we generate a set of initial solutions (chromosome strings) as shown in Fig. 11.
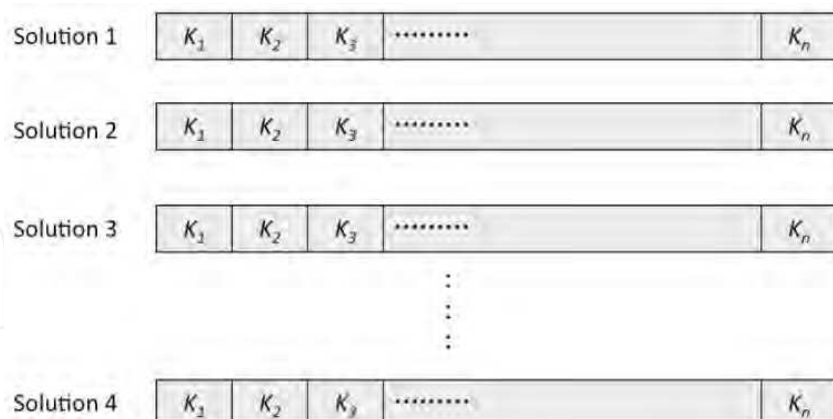

Fig. 11. Encoded chromosome strings

Evaluation

Chromosome string encoding is followed by evaluation. The system objective is to minimize the Total Detection Power (*TDP*). In addition, there are two constraints. One (7) is to constrain the detection power, K_i, the other (8) is to make sure the detection ability of the sensor is greater than a predefined threshold, *a*.

Objective function

$$Min \sum K_i \tag{6}$$

Constraints

$$Max\_K_i \geqq K_i \geqq 0 \tag{7}$$

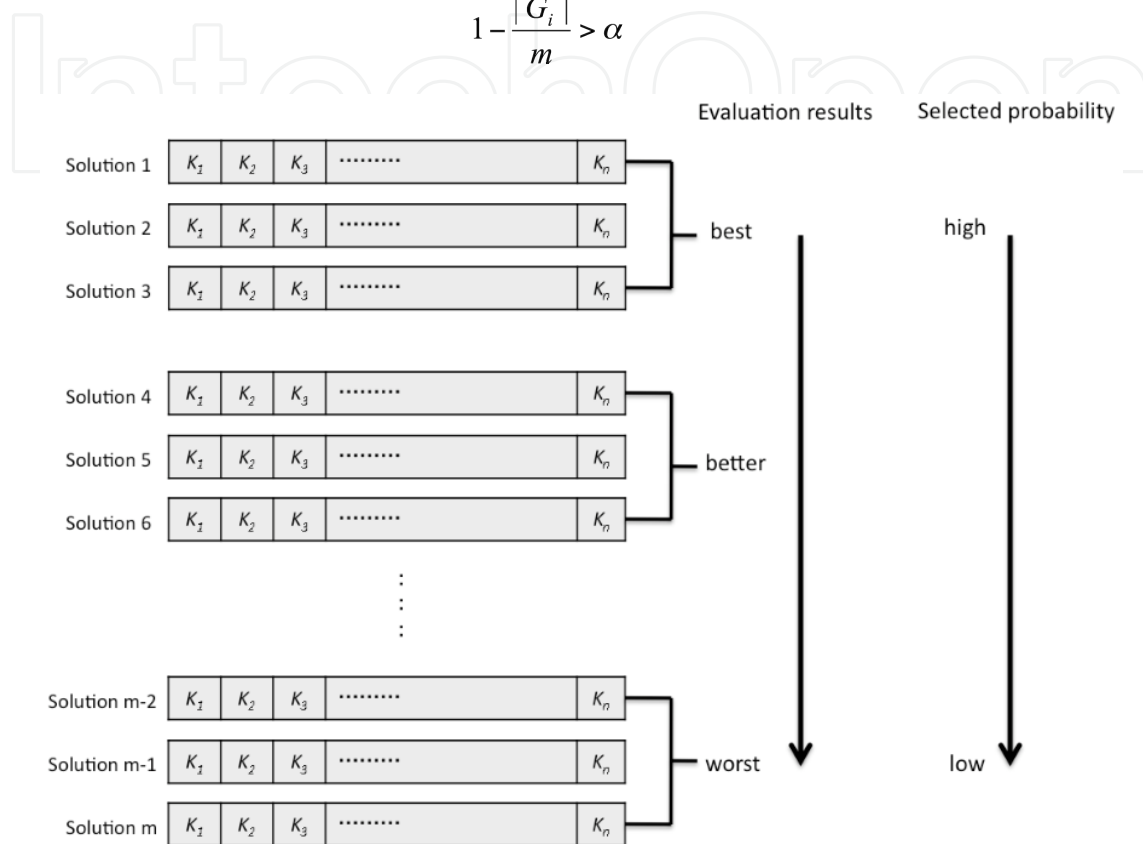$$1 - \frac{|G_i|}{m} > \alpha \tag{8}$$

Fig. 12. The relation between chromosome strings categories and selected probabilities.

Selection

In selection, we classify all chromosome strings into different categories. All those chromosome strings belonging to the same category have similar evaluations. The categories of higher evaluations will have higher probability being selected. Fig. 12 shows the relation between chromosome strings categories and selected probabilities.

Crossover

We design the crossover operation to be two-point crossover. We first randomly choose two positions in a chromosome strings. The offsprings are then produced by exchanging the sub-strings that lie between the two positions. Fig. 13 shows an example of two-point crossover.
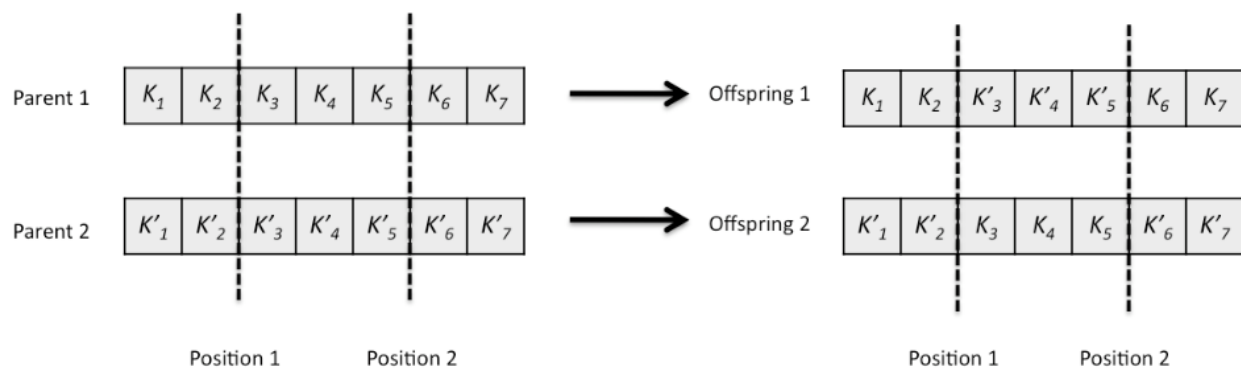
Fig. 13. Example of two-point crossover

Mutation

In mutation, we random choose very few K_i's (low probability) by increasing or decreasing their sensing power. Fig. 14 is an example of mutation. In this example, we random choose elements K_2, K_3, K_4 from parent. K_2 and K_3 become K_2' and K_3' by increasing their sensing powers. On the contrary, K_4 becomes K_4' by decreasing its sensing power.
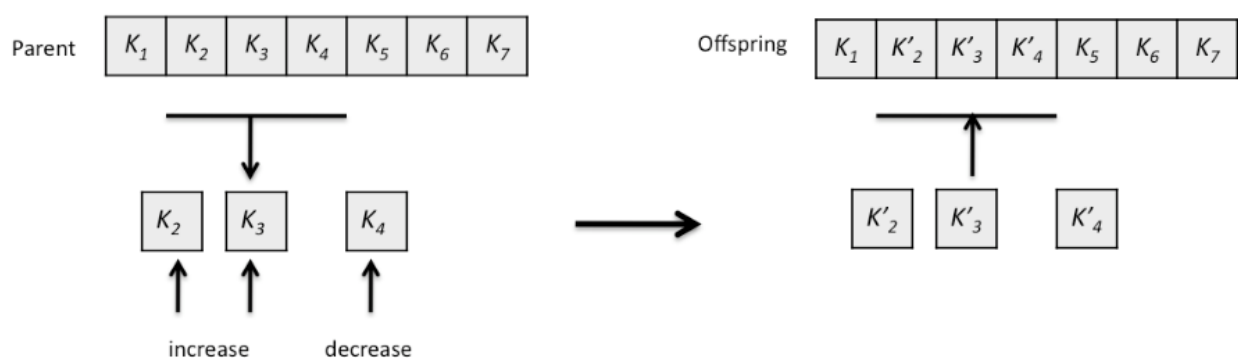

Fig. 14. Example of mutation.

Replacement

As new offsprings are produced, those chromosome string with low evaluation results will be replaced by the new offsprings with high evaluation results.

3.6 Detection power adjustment

Eventually, the optimum will be reached after several iterations of Genetic Algorithm. Each sensor then sets the corresponding value in the optimal chromosome string as its detection power. All these values of detection power will be propagated to each of their neighbours through message exchanges. Each sensor will then adjust its detection power according to both the received values and the value computed by its own. At the end of this step, all the detection powers of sensors are determined. Afterwards the optimization process won't be triggered only if some sensors are damaged or the network topology is changed.

3.7 Procedure

The procedure of the proposed methodology is illustrated as follows.

---

1. *Sensor S exchanges messageswith its neighbours and computesthe relative positions of its neighbours.*
2. *Use Voronoi diagram algorithm to calculate the responsible detection ranges of S.*
3. *Establishgrid structure (m grid points) of S.*
4. *Encode chromosome, with Length = n, Element$_i$ = detection power K of sensor S_i , |chromosome| = X.*
5. **forall** *chromosomes***do**
6. **Evaluate function** *(chromosome)*
7. **end for**
8. **while** *Evolution is not finished***do**
9. *operation = random(Crossover || Mutation)*
10. **if** *operation == Crossover* **then**
11. *select two chromosomes asparents according to the evaluation resultsof TDP randomly exchange some elements to produce offsprings*
12. **else**
13. *select a chromosome as parent according to the evaluation result of TDP randomly change some elements to produce offspring(max_$K_i \geqq K_i \geqq 0$)*
14. **end if**
15. **Evaluate function***(offspring)*
16. **if***(the TDP of evaluation result of offspring is better than their parents) andDetection ability of offspring > a***then**
17. *replace parents by offsprings*
18. **else**
19. *replace parents by offsprings with lower probability and give up offspring's with higher probability*
20. **end if**
21. **end while**

Evaluate function*(chromosome)*
1. **for all** *grid point u of sensor S*
2. **for all** *detection power K_i in the chromosome*
3. $\Pr = K_i + \dfrac{Gain}{I} - 20 \log \dfrac{8\pi d}{\lambda}$
4. $P_i(u) = prob[\Pr + N_i > \beta]$
5. **end for**
6. $P(u) = 1 - [\displaystyle\prod_i^n (1 - P_i(u))]$
7. $G = \{u \mid u \in S_i, P(u) \leq \Gamma\}$
8. **end for**
9. *Detection ability =* $1 - \dfrac{|G|}{m}$
10. *TDP =* $\displaystyle\sum K_i$

---

4. Simulations and results

Simulations are based on the following parameters setting: there are 30 to 100 sensors with the same capability randomly deployed in a detection field of 100×100 m^2. The detection power of each sensor is adjustable, the maximum detection power is 15dBm, the detection range is between 0 to 20 meters, the transmission range is 40 meters, the frequency of detection radio wave is 10.525MHz, the sensitivity is -85dBm, the antenna gain is $8dBm$, the threshold of detection ability (a) is 0.8. In performance comparisons, VERA method is further separated into VERA1 (VERA with $\Gamma = 0.7$) and VERA2 (VERA with $\Gamma \approx 0$). VERA1 and VERA2 are compared with MDR (Maximum Detection Range), K-covered ($K = 1$), and Greedy algorithm by simulations. MDR is an algorithm simply used to maximize detection range without any enhancements on detection range adjustment. K-covered and Greedy algorithms are those proposed by (Huang & Tseng, 2003) and (Cardei et al., 2006), respectively. Five simulations are conducted to verify the performances against overlaps of detection ranges, duplicate data amount, total energy consumption, network lifetime and average detection probability.
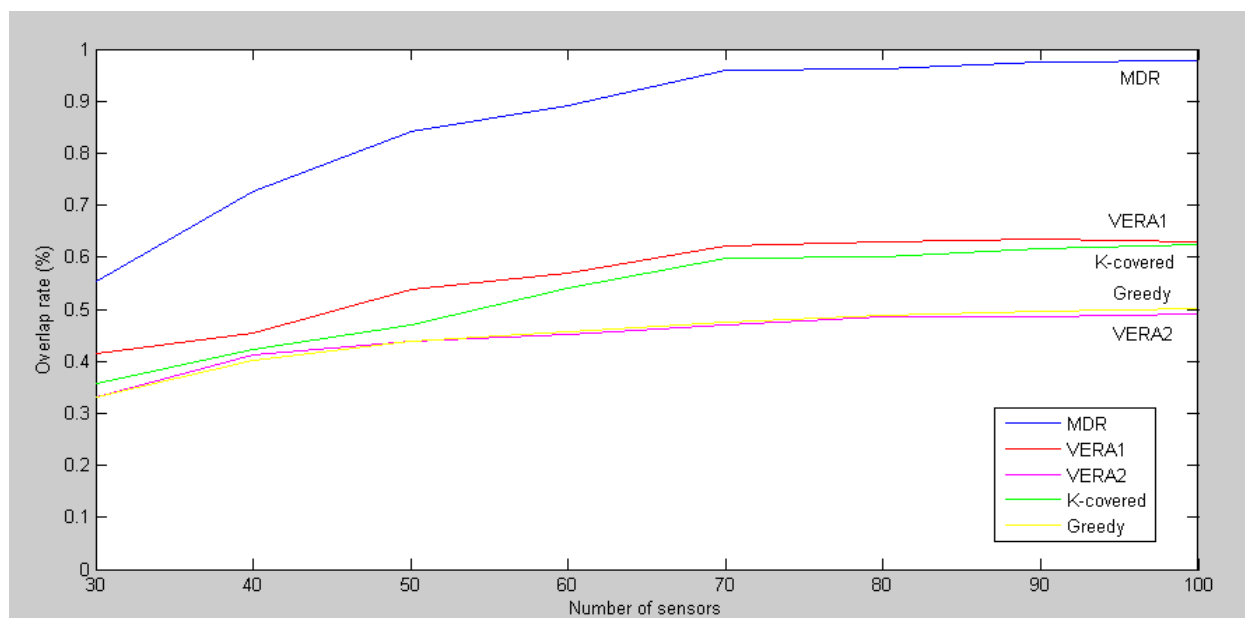

Fig. 15. Comparisons of the ratios of overlapped detection range

Fig. 15 shows the comparisons of the ratios of overlapped detection range of the five methods. As the number of sensors is increased between 30 and 70, the ratios of overlaps of each method increase constantly. This is because when the number of sensors is smaller than 70, there is no sufficient number of sensors to cover the whole detection field. As the number goes beyond 70, the ratios of overlaps of MDR approximate 1.0 because MDR does nothing to detection range adjustment. Whereas the ratios of VERA1 and K-covered stay around 0.6, and those of VERA2 and Greedy stay around 0.5, respectively.

In the second simulation, we define the proportion of duplicate data to be the ratio of the duplicate data amount to the number of detected events. Fig. 16 shows the comparisons of the portions of duplicate data amount of the five methods. It shows that the proportions of VERA1, VERA2 and Greedy are very close to one other. VERA1 has larger duplicate data amount and larger number of detected events. Since there is no detection ability limit on VERA2 and Greedy, it results in smaller duplicate data amount and smaller number of

detected events. *K*-covered has higher portion of duplicate data due to having more overlaps and smaller number of detected events.
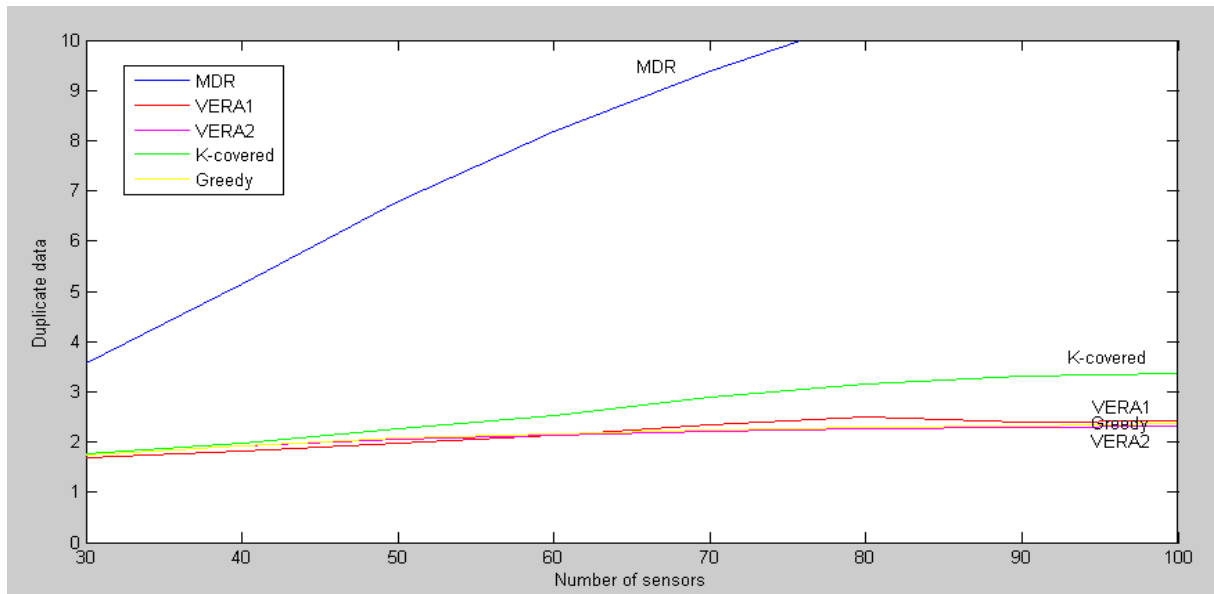

Fig. 16. Comparisons of the portions of duplicate data amount

Fig. 17 shows the comparisons of total energy consumptions of the five methods per round. Since MDR is unable to adjust detection range, the total energy consumption is increased as the number of sensors is increased. As the number of sensors is below 63, the total energy consumption of *K*-covered is less than that of Greedy since *K*-covered has less information exchange than that of Greedy, and *K*-covered has less data needs to be relayed to base stations. As the number of sensors is larger than 63, *K*-cover increases the number of data relays quickly resulting in more energy consumption. Since VERA1 and VERA2 have less information exchange than that of the others, and VERA2 uses less detection power than that of VERA1, therefore VERA2 has the best energy consumption performance.
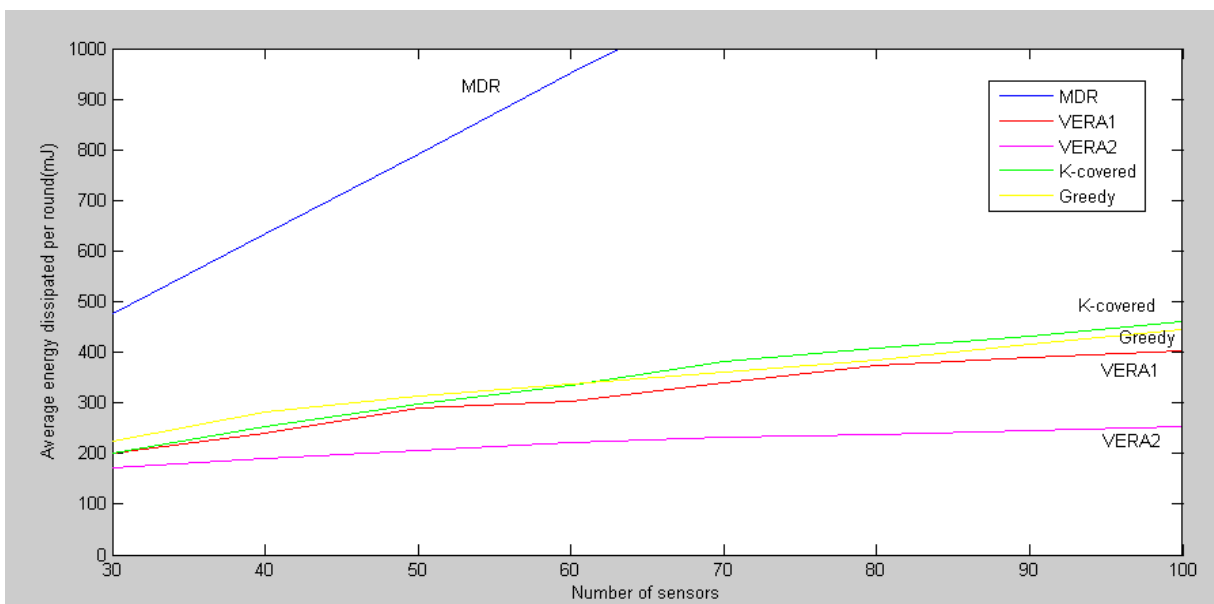

Fig. 17. Comparisons of total energy consumption per round

Fig. 18 shows the comparisons of network lifetime of VERA, K-covered and Greedy methods. At the time the sensor network is deployed at its early stage, there must have many sensors using very high detection powers to reach the borders of detection field. It shows that there are many sensors died at the end of the first 220 rounds. Comparing the number of rounds that the last sensor died, we have VERA2 (940 rounds) > Greedy (890 rounds) > K-covered (880 rounds) > VERA1 (700 rounds). Comparing the number of rounds that the last ten sensors survived, we have VERA2 (700 rounds) > Greedy (680 rounds) > K-covered (670 rounds) > VERA1 (650 rounds).
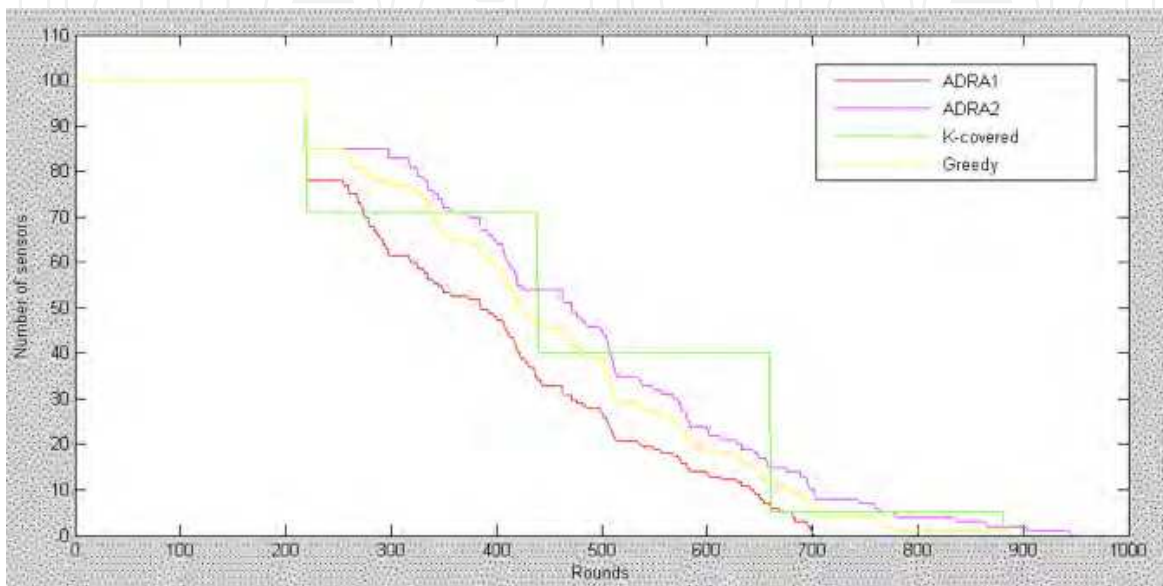

Fig. 18. Comparisons of network lifetime

Fig. 19 shows the comparisons of average detection probability of the detection field of the five methods. As the number of sensors is greater than 70, the average detection probability of VERA1 is very close to 0.7. It is 10% higher than that of K-covered, VERA2 and Greedy. The average detection probability of MDR is almost 0.9 due to its maximum detection power.
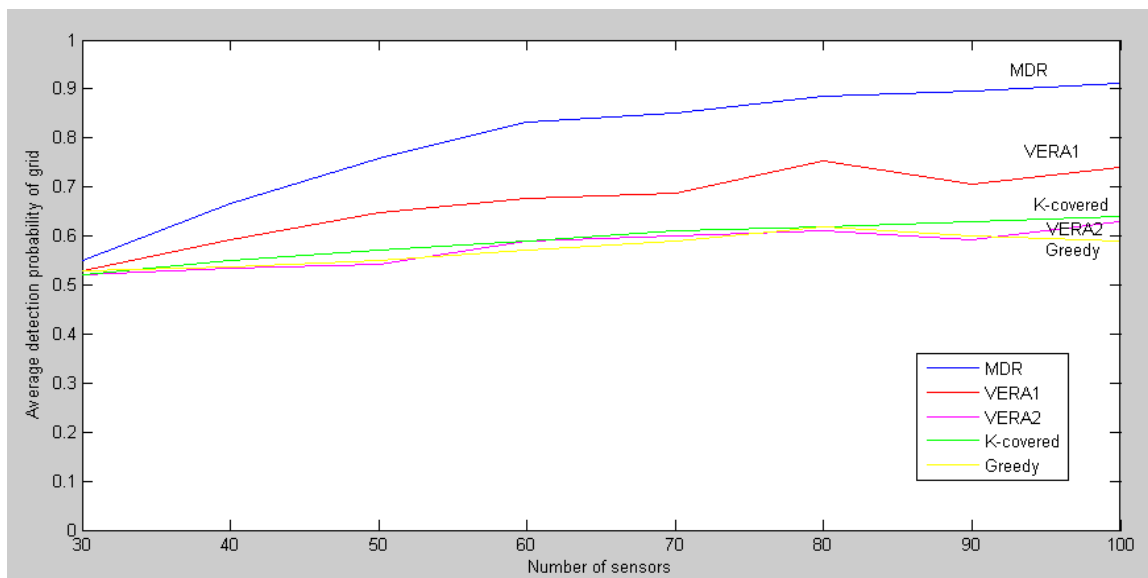

Fig. 19. Comparisons of average detection probability of the detection field

5. Conclusions

In this paper we introduced a framework of five-step methodology to carry out detection range adjustment in a wireless sensor network. These steps are position determination, detection range partition, grid structure establishment, detection power minimization, and detection power adjustment. We proposed a Voronoi dEtection Range Adjustment (VERA) method that utilizes distributed Voronoi diagram to delimit the responsible detection range of each sensor. All these adjustments are under the guarantee that the detection abilities of sensors are above a predefined threshold. We then use Genetic Algorithm to optimize the optimal detection range of each sensor.

Simulations show that the proposed VERA outperforms Maximum Detection Range, *K*-covered and Greedy methods in terms of reducing the overlaps of detection range, minimizing the total energy consumption, and prolonging network lifetime, etc.

6. References

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Energy Management

Edited by Francisco Macia Perez

Forecasts point to a huge increase in energy demand over the next 25 years, with a direct and immediate impact on the exhaustion of fossil fuels, the increase in pollution levels and the global warming that will have significant consequences for all sectors of society. Irrespective of the likelihood of these predictions or what researchers in different scientific disciplines may believe or publicly say about how critical the energy situation may be on a world level, it is without doubt one of the great debates that has stirred up public interest in modern times. We should probably already be thinking about the design of a worldwide strategic plan for energy management across the planet. It would include measures to raise awareness, educate the different actors involved, develop policies, provide resources, prioritise actions and establish contingency plans. This process is complex and depends on political, social, economic and technological factors that are hard to take into account simultaneously. Then, before such a plan is formulated, studies such as those described in this book can serve to illustrate what Information and Communication Technologies have to offer in this sphere and, with luck, to create a reference to encourage investigators in the pursuit of new and better solutions.

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