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Energy-Efficient *k*-Coverage for Wireless Sensor Networks with Variable Sensing Radii

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Abstract— **Wireless Sensor Networks (WSNs) consist of spatially-distributed autonomous sensors that can cooperatively monitor physical and environmental conditions. Because of sensors' resource-constraints in terms of size, power, and bandwidth, one of the fundamental objectives in WSNs is improving energy-efficiency. In this paper, utilizing sensors with variable sensing radii, we propose a group-based technique to obtain energy-efficient *k*-coverage based on our previous work with the Delaunay-Triangulation-based *1*-coverage algorithm. Our sensing-radii optimization technique ensures full coverage and attains nearly-optimal energy consumption in sensing. Furthermore, our *ns-2* simulations confirm that the group-based *k*-coverage reduces sensing energy consumption and maintains a sound coverage ratio for reliable surveillance.**
Key words: wireless sensor networks, coverage, energy-efficiency

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are collections of large numbers of nodes with radio communications, sensing, and low-power processing capabilities. One of the fundamental objectives of WSNs is to provide continuous surveillance to ensure that each point therein is monitored by at least one sensor. In order to provide better accuracy and fault-tolerance, some applications, such as emergency response, military surveillance, and disaster-recovery, require *k*-coverage ($k > 1$), which means that each point in the target area should be monitored independently by k sensors.

Due to sensors' energy constraints, it is important to dynamically configure WSNs by using sleep/wakeup scheduling, or by varying sensing/transmission radii. Such dynamic configuration helps to both minimize energy consumption and ensure required quality of surveillance [22]. Large sensing radii increase energy consumption because they require more sophisticated filtering and signal-processing methods to improve the signal-to-noise ratio and achieve the desired confidence level [27]. Thus, adjustable sensing radii allow for reduced energy consumption by eliminating redundant coverage.

Reliable surveillance and energy-efficiency can be guaranteed by optimizing sensing radii. Due to resource constraints and the wide-spread deployment of sensor networks, a distributed algorithm which achieves global optimality and minimal overhead is preferred. To address these problems, we propose a light-weight, distributed algorithm for dynamic configuration of sensing radii with the following features:

- A distributed algorithm based on one-hop information
- Guaranteed *k*-coverage
- Energy-efficiency in sensing

In our previous work [21], we configured sensors' sensing radii to maintain efficient *1*-coverage based on Delaunay Triangulation. In this paper, we are proposing a group-based technique to obtain *k*-coverage with the same energy-efficiency objectives. Furthermore, our *k*-coverage algorithm can be applied to any *1*-coverage techniques to easily configure *k*-coverage based on local topology.

The rest of this paper is organized as follows: In Section II, we provide a summary of related work. In Section III, we summarize relevant details of our Delaunay-Triangulation-based *i*-coverage technique from [21]. In Section IV, we propose two grouping algorithms to obtain *k*-coverage and energy-efficiency. We evaluate the performance of our techniques based on the *ns-2* simulator in Section V and conclude this paper in Section VI.

II. RELATED WORK

Some of the earliest research on energy-efficient coverage was done by Slijepcevic and Potkonjak who proposed a NP-complete problem called *Set K-Cover* [17]. Their algorithm selects several mutually-exclusive sets of sensor nodes, with each set covering an entire area. Hsin and Liu [9] discuss node-scheduling and the tradeoff between random and co-ordinated sleep algorithms based on low-duty cycle sensors. Tian and Georganas [19] proposed a scheduling mechanism wherein a node becomes active only if its "sponsored area" is covered by its neighboring nodes; and TGim [7] extended Tian and Georganas' mechanism by considering the realistic signal propagation model. Zhang and Hou discuss a triangulation-based coverage, where equilateral triangulation achieves the best energy-efficiency in sensing [11]. Khan *et al.* proposed a Mobile Traversal Algorithm to form an equilateral triangulation-based coverage using mobile sensors [2]. Coverage has been approached from different perspectives by Meguerdichian *et al.* [18], who developed a technique that sought maximal breach and maximal support paths by using the Voronoi Diagram.

The use of *k*-coverage to improve accuracy and fault-tolerance is examined by various other researchers [8], [10], [23], [26]. Huang and Tseng developed a sufficient and necessary condition for *k*-coverage [10]. In order to configure the networks for *k*-coverage, Wang *et al.* proposed an eligibility algorithm to determine whether it is necessary for certain nodes to become active [23]. Gupta, Zhou, and Das designed a greedy *k*-coverage algorithm based on the "K-Benefit" value
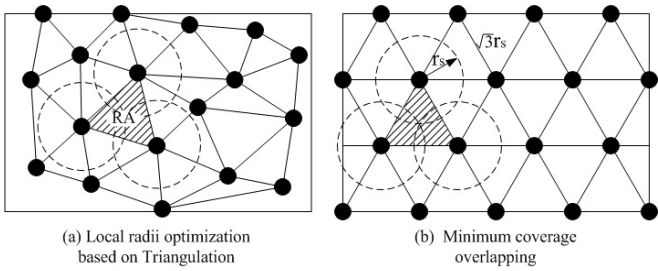
(a) Local radii optimization based on Triangulation   (b) Minimum coverage overlapping

Fig. 1. Triangulation-based Sensing Radii Optimization

Fig. 2. Construction of DT Based on One-hop Neighbors

of each candidate path [26]. Hefeeda and Bagheri illustrated the same problem as a set system in which optimal hitting sets correspond to optimal k-coverage solutions [8].

Recently, researchers have recognized the need to develop integrated approaches for both coverage and connectivity. PEAS [25] addresses that challenge by using a "probabilistic probing." Shakkottai, Srikant, and Shroff [16] examine the probabilistic bounds that both coverage and connectivity can be attained if unreliable sensor nodes have been deployed on a given grid. Wang et al. [23] show that full coverage implies connectivity if the transmission radius is at least two times greater than the sensing radius.

To further reduce redundant coverage, sensors with variable-sensing radii have been used. Wu and Yang [24] propose a coverage algorithm that uses sensors with maximum, medium, and small-sensing radii according to network topology. Cardei et al. [3] propose an algorithm and a model of continuously-adjustable sensing radii in order to identify mutually-exclusive sensor covers with optimal sensing ranges. Other approaches to this problem include those by Dhawan et al. [6] and Zhou et al. [27] based upon Linear Programming and the Voronoi Diagram, respectively.

Our approach is distinct from that of other researchers in several respects. First, we use a group-based technique to extend any existing 1-coverage algorithm into k-coverage. Secondly, we achieve energy-efficiency and guarantee full k-coverage with simple heuristics and only one-hop information. Thirdly, our approach can be combined with other scheduling-based coverage techniques [17], [19] by adjusting the sensing radii within each mutually-exclusive set of sensor nodes.

III. DELAUNAY-TRIANGULATION-BASED 1-COVERAGE

For the sake of completeness we summarize relevant details of our paper on 1-coverage: a distributed algorithm to approximate Delaunay Triangulation and a heuristic to optimize sensing radii for energy-efficiency [21].

To optimize sensing radii locally, a triangulation is used to construct a planar graph based on sensor deployment. A *Responsible Area (RA)* is represented by a triangle in the graph (Fig. 1-a). Each triangularly-shaped *RA* requires coverage to be provided by a single sensor at each of the three vertices of the triangle, for a total of three sensors per *RA*. To optimize sensing coverage locally based on each *RA*, triangulation is essential. For sensor with identical sensing radius, r_s (Fig. 1-b), Zhang and Hou [11] showed that the minimal redundant coverage is obtained with equilateral triangulation, where each
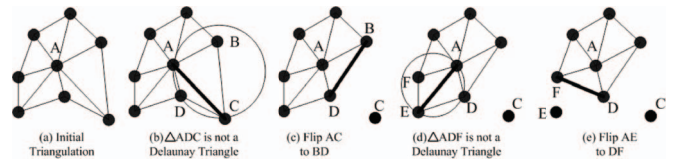
edge is $\sqrt{3}r_s$. This requires consistent distances between adjacent nodes, which is not feasible in random deployment of sensors. With that in mind, we chose Delaunay Triangulation to achieve a nearly-optimal result for coverage.

The distributed algorithms to compute Delaunay Triangulation proposed by Li et al. [12] and Liebeherr, Nahas, and Si[13] require the sensors to have knowledge of nodes located multiple hops away, or had a slow convergence time. We proposed a lightweight algorithm that locally approximates DT using only one-hop neighbor information.

A. One-Hop Approximation of Delaunay Triangulation

Delaunay Triangulation (DT) [4], the dual of the Voronoi Diagram, has the following characteristics:

- "Fat triangles," in the sense that the minimum angle of any Delaunay triangle is as large as possible; and
- The Empty Circle Property, defined as a circle that runs through the vertices of any triangle with no other vertex inside the circle.

We illustrate our algorithm with an example. Our algorithm is based on the centralized edge-flipping algorithm [4]. In our algorithm, each node maintains a list of its one-hop neighbors ($NeighborList$). After an arbitrary triangulation is constructed (Fig. 2-a), each node independently tests its adjacent triangles to determine whether they all satisfy the Empty Circle Property. If an adjacent triangle cannot satisfy the Empty Circle Property, the corresponding edge is flipped. For example, in Fig. 2-b, $\triangle ACD$ is, at first, a non-Delaunay Triangle because point B lies inside of $\triangle ACD$'s circumcircle. Then, AC is flipped to DB, and point C is deleted from A's $NeighborList$. The result is the formation of the Delaunay Triangle $\triangle ABD$ as shown in Fig. 2-c. In Fig. 2-d, $\triangle ADE$ is identified as a non-Delaunay Triangle and, similarly, to make the conversion, AE is flipped to DF and point E is eliminated from A's $NeighborList$. The final result is the creation of $\triangle ADF$, with no other points located inside its circumcircle as shown in Fig. 2-e. The edge-flipping process continues until A's adjacent triangles can all be classified as Delaunay Triangles.

The one-hop approximation of DT can be implemented easily on sensors with low communication and computation overhead; however, with only one-hop information, the resulting triangulation may differ from the traditional DT. We showed that our local approximation of DT is equivalent to the traditional DT, provided that: (1) the area can be completely covered by the maximum sensing radius; and (2) the sensors satisfy $2R_s \le R_x$, where R_s and R_x represent the maximum sensing radius and the maximum transmission radius, respectively [21].

Condition (1) is a basic requirement for any reliable surveillance and condition (2) holds for most hardware. For example, MICA sensors have a sensing range of 2-6m and a transmission range of 30m [1]. Furthermore, $R_x \geq 2R_s$ is commonly assumed to obtain connectivity with full coverage [11], [23]. Our algorithm obtains an accurate DT when the above conditions are satisfied.

B. DT-Based Sensing Radii Optimization

We used a local heuristic to optimize sensing radii based on each triangle and a quadratic sensing energy model (kr_s^2 where r_s is the sensing radius and k is a constant). We showed that the energy consumption of the three sensors at the vertices of each triangle is minimized when their sensing discs intersect at the circumcenter of the triangle ($\sum_{j=1}^{3} x_j/3, \sum_{j=1}^{3} y_j/3$) [21]. The same principle can also be applied to other energy models.

Our heuristic for sensing radii optimization is as follows:

- *Step 1:* Each sensor calculates the optimal sensing radii for each of its adjacent Delaunay Triangles;
- *Step 2:* Each sensor chooses the largest optimal sensing radius among those calculated in *Step 1*.

Full coverage is a fundamental requirement for reliable surveillance. In *Step 2* of our heuristic, local coverage is attained by selecting the largest optimal radius among all adjacent triangles; however, that selection does not necessarily ensure full coverage across the target area. We showed that our DT-based radii optimization can guarantee full coverage if there is no "hole" in the initial deployment [21].

IV. GROUP-BASED k-COVERAGE

For applications in military surveillance and emergency response, k-coverage ($k > 1$) is usually required in order to obtain more accurate data and better fault-tolerance. In a navigation system where the sensor networks are deployed to estimate the location of a moving object, 2-coverage has to be guaranteed since two measurements from different sensors to the same object are required for triangulation [14]. One way to provide 2-coverage is a partition of the network with 2 mutually exclusive groups where each group has a complete coverage. To obtain the best energy efficiency, the partition of each group has to be fair and adaptive to the local topology. Therefore, we propose two efficient solutions based on the probability and local topology. Features of our technique are:

- compatible with existing *1*-coverage algorithms;
- capable of maintaining coverage and energy-efficiency;
- easily configurable with k.

The general concept of our group-based technique involves separating all sensors into k mutually exclusive groups. Each group uses the DT-based *1*-coverage algorithm to optimize its sensing range. Then, by layering the k groups, k-coverage can be achieved. During DT construction, each node will only keep in its $NeighborList$ the neighbor nodes with the same group I.D. as itself; then, all k layers of *1*-coverage can be simultaneously generated by k groups through the DT-based optimization. In order to easily adjust k for various service requirements, a simple, distributed grouping technique is necessary. Furthermore, in order to maintain energy-efficiency and load-balancing, all k groups should have the same number of sensors and the same distribution across the target area.

A. Probability-Based Approach

The probability-based algorithm is a straightforward approach to form k independent groups. It allows each sensor to select any group I.D. between 1 and k with the same probability of $1/k$. To study the distribution of each group, we assume that sensors are deployed according to the Homogenous Poisson Point Process (HPPP) with density λ. HPPP is commonly used in modeling sensor networks for their initial placement and it is a standard model to investigate point processes that are neither completely random nor regular. Then, we will show that each group of sensors follows the same distribution with density denoted by λ/k and the expectation of the group size equals n/k (*Theorem 1 & 2*). The technique we used in our proofs can be found in similar stochastic process and its applications, such as [5].

Definition 1: Homogenous Poisson Point Process (HPPP): On a two-dimensional space Ω with points, $N(A)$ is a counting measure (number of points) of a bounded Borel set A ($A \in \Omega$) and $\sigma(A)$ denotes the Lebesgue measure of set A. The spatial distribution of points across Ω is an HPPP if and only if: (1) $N(A)$ is the Poisson Distribution; and (2) $N(A_i)$ and $N(A_j)$ are independent for any disjoint set A_i and A_j.

Lemma 1: If the original point process is an HPPP, for group $l(l \in 1..k)$, $N_l(A_i)$ and $N_l(A_j)$ are independent for any disjoint A_i and A_j.

Due to the HPPP, $N(A_i)$ and $N(A_j)$ are independent for any disjoint A_i and A_j. Because each node randomly joins the group, $N_l(A_i)$ and $N_l(A_j)$ ($l \in 1..k$) are still independent for any disjoint A_i and A_j; hence, *Lemma 1* holds.

Lemma 2: If the original point process is an HPPP with density λ, then $N_i(A)(A \in \Omega)$ is the Poisson Distribution with density λ/k for group $i(i \in 1..k)$.

Proof: We assume that $1 - p$ is the probability of any point in the original distribution joining group i; therefore:

$$
\begin{aligned}
P_r(N_i(A) = n) &= \sum_{j=0}^{\infty} (P_r(N(A) = n+j)\binom{n+j}{n}(1-p)^n p^j) \\
&= \sum_{j=0}^{\infty} (\frac{e^{-\lambda|A|}(\lambda|A|)^{n+j}}{(n+j)!} \frac{(n+j)!}{n!j!}(1-p)^n p^j) \\
&= \frac{e^{-\lambda|A|}(\lambda|A|)^n}{n!}(1-p)^n \sum_{j=0}^{\infty} \frac{(\lambda|A|p)^j}{j!} \\
&= \frac{e^{-\lambda|A|}(\lambda|A|)^n}{n!}(1-p)^n e^{\lambda|A|p} \\
&= \frac{e^{-(1-p)\lambda|A|}((1-p)\lambda|A|)^n}{n!} = \frac{e^{-\rho|A|}(\rho|A|)^n}{n!}
\end{aligned}
$$
(1)

According to Equation (1), $N_i(A)$ is a Poisson Distribution with density ρ where $\rho = (1-p)\lambda$. Because $1/k$ is the

probability of each sensor joining group i, $N_i(A)$ is a Poisson Distribution with the density of λ/k for group i. ∎

Theorem 1: If the original point process is an HPPP with density λ and each sensor randomly joins a group $i \in 1..k$ with the probability of $1/k$, then group $i(i \in 1..k)$ is also an HPPP with density λ/k.

Proof: According to *Definition 1*, a point process is an HPPP if and only if conditions (1) and (2) are satisfied. Therefore, based upon *Lemma 1 & 2*, group $i(i \in 1..k)$ is an HPPP with density λ/k. ∎

Theorem 2: If sensors randomly join group $i(i \in 1..k)$ with a probability of $1/k$, then all groups have the same expectation of group size.

Proof: $1/k$ is the probability of each sensor joining group i. Suppose ξ is the random variable representing the size of group i, and the number of points in Ω is N. According to Binomial Distribution, $P_B(\xi = x) = \binom{N}{x}(1/k)^x(1 - 1/k)^{N-x}$, and hence $E(\xi) = N/k$. So, the expectation of the group size is the same for all groups. ∎

The probability-based algorithm ensures the same group size and distribution probabilistically by assuming an HPPP for initial sensor deployment; however, it may not be feasible to place sensors in a certain regular manner (*i.e.* HPPP). Furthermore, information on the initial sensor placement may not be available and the topology of sensor networks may be dynamically changed into any random formation due to various environmental conditions and unbalanced work-loads. Additionally, in order to obtain better performance in energy-efficiency and load-balancing, more deterministic properties in group size and distribution are preferred.

B. Grid-Based Approach

Different from the complete random group-formation in the probability-based approach, an alternative way of forming groups is by using full coordination among all sensors. However, such an approach is impractical in sensor networks due to resource constraints and scalability issues. Thus, we propose a grid-based approach, which utilizes limited coordination among one-hop neighbors in order to obtain a more deterministic property under arbitrary network topology.

In the grid-based approach, we apply the randomized group assignment on a much smaller scale than the probability-based approach. The basic idea is to divide the area into contiguous cells where each cell contains k or fewer sensors. Then, we randomly assign group I.D.s (from 1 to k) to sensors within each cell. The group size is N/k for a total of N sensors, if all cells contain exactly k sensors. Furthermore, because WSNs are generally assumed to be densely-deployed, each cell will be small enough to allow the grid-based algorithm to attain the same distribution for each group. For example, as illustrated in Fig. 3-a, where sensors are more densely-deployed, the cells are much smaller than Fig. 3-b. Then for any arbitrary area $\mathbb{A}$ (*i.e.* the circle in Fig. 3-a and b) and two groups G_i & G_j, the relative variation between those two group sizes in $\mathbb{A}$ is $\frac{|G_i|_{\mathbb{A}} - |G_j|_{\mathbb{A}}}{|G_i|_{\mathbb{A}}}$. Because only those cells that intersect $\mathbb{A}$'s border (shaded cells) will contribute to the variation of group
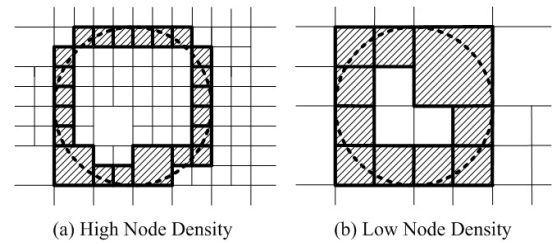

(a) High Node Density   (b) Low Node Density

Fig. 3. Grid Formation with Different Node Densities
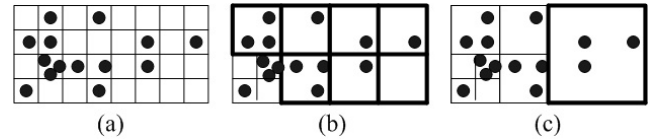

(a)   (b)   (c)

Fig. 4. Cell-Merging Process ($k = 3$)

sizes, the sizes of all groups in $\mathbb{A}$ are almost equal in Fig. 3-a. Therefore, as long as the network is densely-deployed, the grid-based approach can obtain desirable properties in group size and distribution under any sensor topologies.

Our grid-based algorithm consists of two phases. The first phase is to construct the grid with each cell containing no more than k sensors. In the second phase, a random method or heuristic is used to assign group I.D.s based on each cell. Obviously, if division is continued until each cell contains zero or one sensor, the grid-based approach becomes similar to the probability-based approach.

Grid construction by division has two drawbacks. First, it is slow because the initial cell (the entire target area) has to be divided repeatedly into smaller cells until each cell contains only k or fewer than k sensors. Secondly, it is not feasible to distributively implement division-based construction with local topology information. To alleviate those problems, we use a merging process in order to distributively construct the grid in a short time from one-hop information. The grid is initially pre-defined with cells of the same size. Those cells should be small enough that none of them contain more than k sensors (Fig. 4-a). Each sensor identifies its residual cell based on its location information which is available through GPS or other localization mechanisms (for example, see [15]). If the number of sensors in four quadrants is fewer than or equal to k, then those four quadrants are merged into one rectangular cell (Fig. 4-b). By continuously merging four smaller quadrants into one larger cell, the number of sensors contained in all cells in the final grid will exactly equal k, or nearly k (Fig. 4-c). If the network is densely deployed, cells will stop growing before their sizes exceed one-hop range; thus, the merging process can quickly compute the grid with local information.

After the grid is formed, each cell will contain exactly k or fewer than k sensors. In the second phase, each sensor's group I.D. will be determined within its rectangular cell. For a cell S and $|S|$ representing the number of sensors in S,

1) If $|S|=k$, $1..k$ is randomly assigned to k nodes in S;
2) If $|S|<k$, all sensors in S join groups from $1..k$ with a probability that is inversely proportional to the size of each group in their one-hop neighborhood.

● Group 1   ⊘ Group 2   ○ Group 3
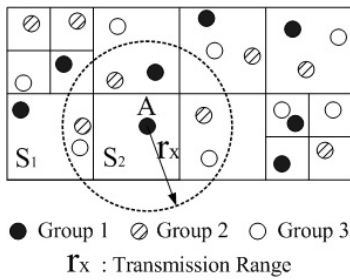
$\mathbf{r_x}$: Transmission Range

Fig. 5.   Grid-Based Group Assignment for 3-Coverage

In Fig. 5 ($k=3$), cell S_1 has three sensors, thus it randomly assigns each sensor with a group I.D. from 1..3 according to rule (1). Cell S_2 has one sensor A, hence sensor A uses rule (2) to join group 1 based upon group sizes in its neighborhood. Within sensor A's one-hop range, there is one sensor in group 1, three sensors in group 2, and two sensors in group 3; so sensor A will have the highest probability of joining group 1.

V. Performance Evaluation

Our DT-based *1*-coverage algorithm and group-based *k*-coverage algorithm were implemented using the *ns-2* simulator. To evaluate their energy-efficiency and quality of coverage, we used standard metrics as in [24], [27], including average sensing radius (*Meters*), average sensing power (*Watts*), and coverage ratio (%). For the simulation setup, we used $50 \sim 250$ randomly-deployed sensors on a 50×50 grid. We adopted a similar quadratic energy model ($0.01r_s^2$) and maximum sensing radius ($10m$ and $20m$) from [3]. Each scenario was simulated for 500 seconds and results were collected from 20 trials with randomly-generated topologies.

A. *1-Coverage Algorithm*

To evaluate our DT-based *1*-coverage algorithm, we compared it to Wu's Variable Sensing Range algorithm (VSR) [24], which we also implemented in the *ns-2*. Our previous work [21] has studied the DT-based *1*-coverage technique regarding to its performance on energy balancing and lifetime. In this paper, we focus on the quality of coverage and energy efficiency. We collected the coverage ratios, and the averages of the sensing radii and sensing energy based on two sets of maximum sensing radius ($10m$ and $20m$) in order to show the tradeoff between density, energy consumption, coverage ratio. The larger sensing radius may be advantageous for lower density; but with higher density, it consumes much higher energy and may not provide significantly better coverage than the smaller sensing radius does. As in Fig. 6-c, sensors with $20m$ radius has coverage improved by less than 0.2% compared to sensors with $10m$ radius when more than 200 nodes are used in our topology; however, this marginal gain is obtained at the cost of almost 3 times more of average energy consumption.

Compared with our DT-based algorithms, VSR yielded a nearly constant average sensing radius as density increases with the $10m$ maximum sensing radius (in Fig. 6-a). VSR's behavior can be explained by its use of static radii assignments which are based on predetermined locations; however,

with a dynamic radii optimization, DT-based algorithms can effectively reduce the sensing radius with various network densities. A similar behavior can be observed with a maximum sensing radius of $20m$, where the DT-based algorithm reduces the average sensing radius in VSR by almost 10%. In Fig. 6-b, with a quadratic sensing model of $0.01r_s^2$, a more apparent energy-savings can be observed using the DT-based algorithm. Although VSR shows better performance in the case of 25 nodes and 10m maximum sensing radius (shown in Fig. 6-a and b), its coverage rate, at the same density and maximum sensing radius, is less than 65% (shown in Fig. 6-c). In contrast, the DT-based algorithm yields considerable improvements in surveillance quality as it provides more than 85% coverage at all density levels.

B. *k-Coverage Algorithms*

Since there are no other *k*-coverage algorithms based on optimizing sensors' sensing radii, we evaluate only the group-based *k*-coverage algorithms using DT-based sensing radii optimization. Both probability and grid-based approaches are compared with up to 3-coverage. Our evaluation metrics included the coverage ratios and the averages of the sensing radii and sensing energy. In Fig. 7-a, a correlation is observed between the levels of coverage and sensing radii, where a higher level of coverage requires larger sensing radii. This is because node density decreases in each group with a higher level of coverage. Additionally, in the process of reaching 2-coverage, the grid-based algorithm resulted in a better average radius than the probability-based algorithm. The grid-based algorithm obtained an average sensing radii that is about 6% lower than the probability-based algorithm. Similarly, in obtaining 3-coverage, the grid-based algorithm outperforms the probability-based algorithm and its average sensing radius is about 11% lower. The explanation lies mainly in the fact that grid-based approach uses a local collaboration mechanism to attain more balanced group formation and hence, improves the radii assignment in randomly deployed networks. Fig. 7-b illustrates the average sensing energy consumption of 2 and 3-coverage and shows a behavior similar to that which is described above. Therefore, with sufficient sensors deployed, the grid-based approach offers improved optimization of sensing radii based on local topology. Furthermore, as shown in Fig. 7-c, surveillance quality was evaluated by comparing the coverage ratio, which shows that both probability and grid-based mechanisms can achieve almost the same coverage ratio.

VI. Conclusion

The Delaunay Triangulation-based algorithm that uses variable-sensing radii can effectively address and mitigate problems associated with reliable coverage and energy-efficiency. Our approach includes the use of a light-weight, distributed algorithm to approximate Delaunay Triangulation as a basis for estimating the optimum radii to obtain *1*-coverage and energy-efficiency. Based on the *1*-coverage technique, we developed two methods, a probability-based approach and a grid-based approach, to easily configure *1*-coverage into any level of multiple coverage. Our *k*-coverage technique
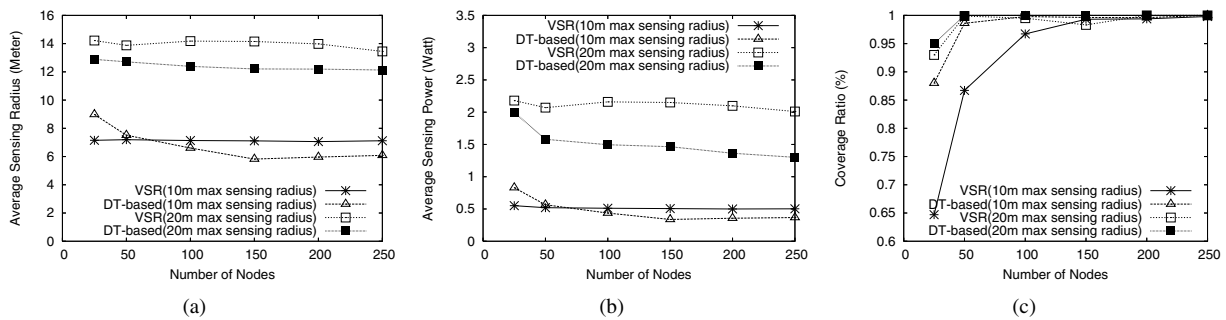
Fig. 6.   *1*-Coverage: (a) Average Sensing Radius (b) Average Sensing Power (c) Coverage Ratio
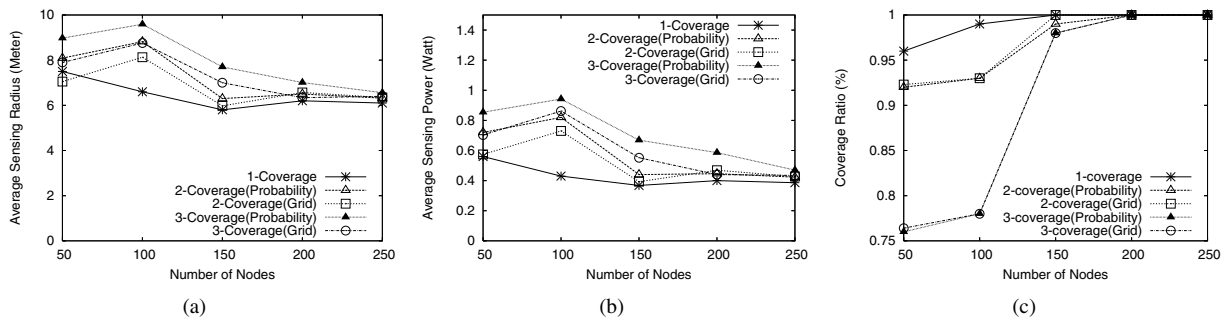

Fig. 7.   *k*-Coverage: (a) Average Sensing Radius (b) Average Sensing Power (c) Coverage Ratio

is based on a partition of mutually exclusive groups with same distribution. The goal is to develop a technique that is generic to any *1*-coverage algorithm and still preserves the original energy-efficiency obtained from the *1*-coverage algorithm. We have shown comparisons of our grouping-based technique using *1*-coverage techniques proposed by us and other researchers. Our performance analysis has shown that different *1*-coverage techniques can be extended to *k*-coverage with good-coverage and energy-efficiency using our *k*-coverage technique. Furthermore, our *ns-2*-based experimentation demonstrates that the DT-based *1*-coverage technique is more effective in maintaining coverage with energy-efficiency at various network densities, and the grid-based approach to the *k*-coverage problem performs better than probability based approach because it involves limited coordination among one-hop neighbors which allows it to attain more desirable features with arbitrary sensor-deployment.

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