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Highlights

- We propose an intelligent wake-up scheme for information fusion in wireless sensor network surveillance.
- We propose a node importance based information fusion scheme.
- We conduct extensive experiments using the real world data set.

Energy-aware Scheduling for Information Fusion in Wireless Sensor Network Surveillance

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Abstract

Effective energy control while maintaining reliable monitoring performance becomes a key issue in wireless sensor networks (WSNs) based surveillance applications. While importance difference of surveillance zone, limited energy and dynamic network topology pose great challenges to surveillance performance. It is necessary to adjust sensor nodes awakening frequency dynamically for information fusion. Thus an energy-aware scheduling with quality guarantee method named ESQG is proposed in this paper which considers sensor nodes residual energy, different importance degrees of the surveillance zone and network topology comprehensively. It first uses a Voronoi diagram to determine the effective scope of each sensor node and then calculates node importance according to its residual energy and the importance degree of the effective scope. Then ESQG utilizes the importance of individual sensing scope and current forwarding costs to further compute node importance and awakening frequency for information fusion. In this way, ESQG can dynamically adapts each nodes awakening frequency to its dynamic network topology and importance degree of each individual sensing scope. The nodes are then turned on stochasticlly via the node awakening probability and node importance based information fusion is conducted for tar-

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get detection. Besides, an adaptive process of perception factor C is proposed to match actual situation, and automatically change according to the detected data. Experiments results demonstrate that the proposed method ESQG can reduce the number of awakening nodes to a large extent while maintaining high reliability via information fusion.

Keywords: Wireless Sensor Networks, Network topology, Detection Efficiency, Voronoi Diagram

1. Introduction

With the rapid development of integrated circuits, digital signal processing and low-range radio electronics, wireless sensor networks (WSNs) have received great attention for wide application potentials. WSN based applications enlarge human capabilities to remotely interact with the physical world. These applications include battlefield surveillance [1], target tracking [2], home appliances and inventory tracking in which information fusion [3] is needed. For example, in the monitoring of Blue-green Algae Bloom on Lake Tai [4], its physical information (eg., water temperature, water color) can be obtained to predict biological growth and potential ecological disasters via information fusion. However, WSN enjoys some unique characteristics such as limited energy supply. That is because sensor node has a finite energy reserve supplied by a battery and is often unfeasible to recharge the battery, effective energy control while maintaining reliable detection performance is key problem to wireless sensor networks surveillance.

Thus minimizing energy consumption while maintaining system performance via information fusion remains a high priority in designing wireless sensor networks. To prolong the lifespan of a network, sensor nodes are often scheduled to sleep dynamically. While adjacent nodes share common sensing tasks, which implies that not all sensor nodes are required to perform the sensing task in the whole system lifetime. That is to say, as long as there are enough working nodes, the function of the whole system will not be affected by some sleeping nodes. Therefore, if the sensors can be well scheduled, the system lifetime can be prolonged correspondingly; i.e. the system lifetime is prolonged by exploiting redundancy [5]. In order to increase the node energy utilization and lengthen the lifetime of the wireless sensor network (WSN), a novel clustering node sleep scheduling algorithm based on information fusion is proposed in [6]. But these works mentioned above does not consider providing differentiated surveillance services for different importance degree areas while maintaining high enough detection probability to targets. All of them do not consider link fluctuations and other network dynamics. What is more, sleep scheduling mechanism is the most widely used technique for efficiently managing network energy consumption. The author of [7] provides a survey on energy-efficient scheduling mechanisms in wireless sensor networks that has different network architecture than the traditional wireless sensor networks. However, although much more energy can be saved by reducing the working time of sensor module [8], duty cycling usually wastes energy due to unnecessary wakeups, and low-power radios are used to awake a node only when it needs to receive or transmit packets while a power-hungry radio is used for data transmission and information fusion.

As for dynamic network topology, it is still a challenge from the real-world perspective where latency and network lifetime are major concerns. In that light, ORW is the first protocol to effectively employ opportunistic routing in wireless sensor networks [9]. ORW shows that compared to traditional routing schemes opportunistic forwarding decisions can significantly improve data collection performance in asynchronously duty-cycled networks in terms of end-to-end packet latency and energy efficiency, while being more resilient to topology changes. Despite the many benefits over traditional routing schemes, existing opportunistic routing protocols run on top of duty-cycled link layers where all nodes have the same wake-up frequency. As a result, all nodes have the same forwarding costs with regard to latency and energy usage. But nodes play different roles. The closer a node is to the sink, the more packets it has to forward, and hence, the lower its forwarding costs should be. The awakening frequencies should match the role of each node. This is indeed the idea of various adaptive, duty-cycled link layers. However, those targeting opportunistic data collection protocols have only been studied analytically [10], thus lacking validation against the real-world dynamics of low power wireless, or have been designed for static networks and traditional tree-based routing schemes on top of the unicast primitive [11]. While [12] presents Staffetta, the first practical duty-cycle adaptation scheme for opportunistic low-power wireless protocols. It can dynamically adapts each node's wake-up frequency to its current forwarding cost, so nodes closer to the sink become more active than nodes farther away. In this way, Staffetta biases the forwarding choices toward the sink as the neighbor waking up first is also likely to offer high routing progress. However, they also do not consider the difference among the surveillance zone which has great impact on the energy efficiency.

In this work, ESQG (Energy-aware Scheduling with Quality Guarantee) scheme via information fusion is presented, which is an extension of our previous conference paper[13]. In ESQG, every node has a local decision on whether it needs to be turned on or off by dynamic calculation of its importance degree, residual energy and forwarding costs in WSNs. This design is driven by the following requirements: 1) the self-configuration is mandated because it is inconvenient and impossible to manually configure sensor nodes when they have been deployed in hostile or remote working environments; 2) the design should be fully distributed and localized; 3) differentiated surveillance services for different importance zone is necessary while maintaining high performance; 4) current algorithm lacks validation against the real-world dynamics of low power wireless, or have been designed for static networks.

The contributions of this paper are summarized as follows.

1. We propose a Voronoi diagram based method to qualify the importance degree of individual sensing scope, which utilize the difference of surveillance efficiency, effective scope and node residual energy comprehensively. It can provide guideline to conduct intelligent awakening for information fusion in sensor network based surveillance. Besides, an adaptive process

of perception factor C is proposed to match actual situation, and automatically change via the detected data.

2. We propose a intelligent awakening scheme for efficiency scheduling and information fusion to obtain the balance between surveillance performance and energy efficiency via considering both the importance of individual sensing scope and dynamic network topology. In this way, ESQG can dynamically adapts each nodes wake-up frequency to its current forwarding cost and importance of individual sensing scope.
3. Node importance based information fusion is proposed for target detection. The sensor node with the most importance in the cluster is fusion node. Each fusion node makes a final decision at each sample interval according to each member nodes importance. In this way, the information fusion performance can be improved efficiently to maintain high reliability while obtaining energy balance.

The rest of the paper is organized as follows. Related works and an overview will be introduced in Section 2 and 3 respectively. Section 4 presents voronoi diagram based node importance degree computing method. Forwarding costs based node importance computing is introduced in Sections 5. The details of ESQG are discussed in Sections 6 and 7. Simulation results are presented and discussed in Section 8. Concluding remarks are provided in Section 9.

2. Related work

In order to minimize energy consumption while maintaining system performance in WSNs, information fusion and sleep/wake-up schemes are necessary. Information fusion aims to improve surveillance performance and sleep/wake-up schemes aim to adapt node activity to save energy by putting the radio in sleep mode.

Multi-sensor information fusion technology is an emerging technology, which is the foundation of intelligent control. Based on the fact that individual sensor nodes are not reliable and subject to failure and single sensing readings can be easily distorted by background noise and cause false alarms, it is simply not sufficient to rely on a single sensor to safeguard a critical area. In this case, through information fusion, it desires to provide higher degree of coverage in which multiple sensors monitor the same location at the same time in order to obtain high confidence in detection. The authors of paper [14] introduced the definition of multi-sensor information fusion technology from bionic, mathematic and engineering aspects respectively. A reputation-driven information fusion method is proposed in [15], which considered the values of the readings collected by the sensor nodes and eliminate the outliers before fusing information. The authors of [16] provided a comprehensive status of recent and current research on context-based Information Fusion systems, tracing back the roots of the original thinking behind the development of the concept of context. Information fusion is the field charged with researching efficient methods for transforming information from different sources into a single coherent representation, and therefore can be used to guide fusion processes in opinion mining.The authors of [17] present a survey on information fusion applied to opinion mining. An innovative distributed architecture is proposed in [18], which encompassed intelligent sensor nodes, self-configuring real-time communication networks, and a suitable sensor and information fusion system for condition monitoring. Leveraging previous results in the field of cognitive wireless networking, the authors of [19] derive proper decision and fusion strategies. System performance is analyzed in terms of False Alarm/Correct Detection probabilities and energy consumption, quantifying inherent tradeoffs between these performance indicators. A mobile robot positioning method based on multi-sensor information fusion [20] is proposed in this Article to improve the accuracy of mobile robot positioning method. A multi-sensor conflict measure [21] is proposed which estimates multi-sensor conflict by representing each sensor output as interval-valued information and examines the sensor output overlaps on all possible n-tuple sensor combinations. Besides, a sensor fusion algorithm is proposed based on a weighted sum of sensor outputs, where the weights for each sensor diminish as the conflict measure increases. In order to meet user sensing accuracy requirements and obtain energy balance among sensors, [22] propose a collaborative sensor selection method named CSdT. Based on sensor-target distance and sensor correlation, CSdT scheme clusters right sensors in a distributed way for information fusion. However, these methods will be too energy-consuming if the same high degrees of coverage are applied in some non-critical areas.

Duty cycling schemes, passive wake up radios and topology control are usually used to sleep/wakeup sensor nodes. Duty cycling schemes [23] schedule the node radio state depending on network activity in order to minimize idle listening and favor the sleep mode. Some work has been done to adapt the active period of nodes online in order to optimize power consumption in function of the traffic load, buffer overflows, delay requirements or harvested energy [24]. But fixing parameters like listen and sleep periods, preamble length and slot time is a tricky issue because it influences network performance. The authors of [25] proposed an average consensus-based distributed algorithm (ACDA) to distributively schedule the work modes of all sensors using only local information. Unlike most existing studies that use the duty cycling technique, which incurs a trade-off between packet delivery delay and energy saving, [26] did not use duty cycling, avoids such a trade-off. A trade-off between node density and sleep/active nodes are established in [27] which can save energy because at the time of sleep nodes not communicating with any cluster member and head and energy required for the communication is saved. The authors of [28] can get an accurate redundancy degree of one sensor node and adopt fuzzy logic to integrate the redundancy degree, reliability and energy to get a sleep factor. Based on the sleep factor, it furthermore proposes the sleep mechanism. In [29], the sensor nodes are organized into clusters. The sensor nodes in each cluster set their states into sleep/active mode based on their residual energies. However, duty cycling usually wastes energy due to unnecessary wakeups, low-power radios are used to awake a node only when it needs to receive or transmit packets while a power-hungry radio is used for data transmission. When sensors are redundantly deployed in order to ensure good space coverage, it is possible to deactivate some nodes while maintaining network operations and connectivity.

These solutions treat different surveillance zones with the same importance. What is more, in most scenarios such as battlefields, some geographic sections such as the general command center are much more security-sensitive.

Topology control protocols exploit redundancy to dynamically adapt network topology based on applications needs in order to minimize the number of active nodes. Indeed, nodes that are not necessary for ensuring connectivity or coverage can be turned off in order to prolong the network lifetime. In a recent work, the authors of [30] proposed a distributed battery recovery effect aware connected dominating set constructing algorithm for wireless sensor networks. In this algorithm, each network node periodically decides to join the connected dominating set or not. Nodes that have slept in the preceding round have priority to join the connected dominating set in the current round while nodes that have worked in the preceding round are encouraged to take sleep in the current round for battery recovery. Staffetta is proposed in [12] which can dynamically adapt each node's wake-up frequency to its current forwarding cost, so nodes closer to the sink become more active than nodes farther away. However, these works mentioned above does not consider providing differentiated surveillance services for different importance degree areas while maintaining high enough detection probability to targets.

3. System overview

In this paper, "Importance Degree", "Effective Scope","Residual Energy" and "Network Topology" are introduced into ESQG as shown in Fig. 1. In this way, the importance of individual sensing scope is quantified and forwarding costs such as forwarding delay and energy usage are considered. Thus each nodes awakening frequency is obtained and the waken-up probability is decided by quantified value. Bigger such value will be assigned a larger wake-up probability for information fusion. At the same time, the node importance can also obtained via such quantified value. Thus the wake-up sensor nodes (active nodes) are utilized to form sensor node clusters and node importance based information

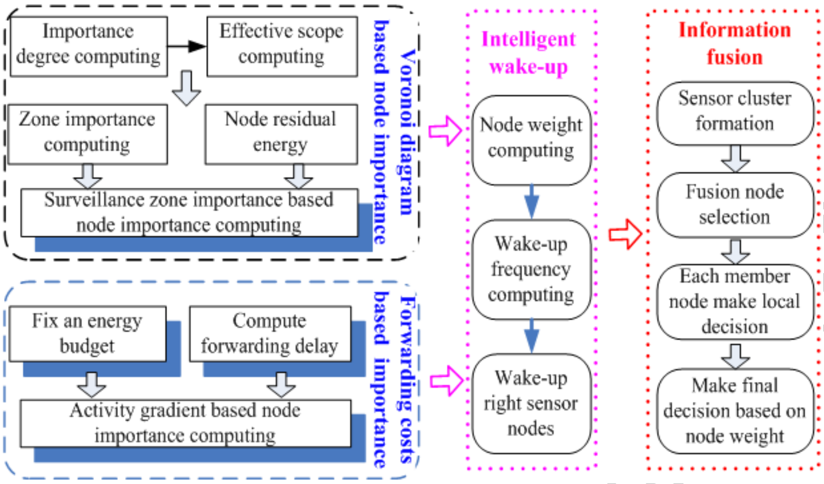

Figure 1: System overview

fusion can be conducted for target detection. Besides, an adaptive process of perception factor C is proposed to match actual situation, and automatically change according to the detected data. The dynamic change of C value can well avoid mistakes due to human factors, adapt to the effects of environmental changes, and response timely. In this way, the number of working nodes is reduced while surveillance performance is kept via information fusion and more energy is saved.

Voronoi diagram based node importance computing. The surveillance zone is first divided into a lot of discrete grids and each grids surveillance efficiency is computed via its impact factor. Then we compute the Voronoi region of sensor node according to Voronoi diagram and a mapping from 2-D dimension region to voronoi region is obtained. Finally, the importance of sensor node is computed by surveillance efficiency, voronoi region and node residual energy.

Forwarding costs based node importance computing. As for dynamic network topology, we initially adjusts the wake-up frequency of nodes to their current forwarding costs. Under such circumstance, an activity gradient is created. The sensor nodes closer to the sink wake up more often and are more

Table 1: Parameter Meanings

Symbol	Parameter meanings
N	Number of the sensor nodes
n	The n-th sensor node
Ω	Sensor nodes set
$\Xi(\Omega)$	Voronoi Diagram
m	The number of forwards
$\Lambda(n_i)$	The forwarding delay of the sensor node n_i
$\hbar$	Transmission time
$\Lambda(\gamma, n_i)$	Rendezvous time of the node n_i
$\Im$	maximum duty cycle
$f(n_i)$	Waking frequency of the sensor node n_i
$\varphi(n_i)$	The importance of the node n_i
α, β	Weight balance parameter

important than those farther away. When a desired network lifetime is given, the maximum fraction of time about the radio's status of each sensor node is decided by such maximum duty cycle. The node importance within the energy budget is caculated.

Intelligent wake-up scheme for information fusion. We propose a intelligent wake-up scheme to obtain the balance between surveillance performance and energy efficiency via considering both the importance degree of individual sensing scope and current forwarding costs. In this way, ESQG can dynamically adapts each nodes wake-up frequency to its current forwarding cost and importance of the sensor node for information fusion.

Node importance based Information fusion. Node importance based information fusion is proposed for target detection and the nodes importance is computed by the importance of individual sensing scope and dynamic network topology. In particular, the sensor cluster is first formed via a simple homogeneous model. The sensor node with the most importance in one circular area is the fusion node and all the other sensor nodes in its circular area are member nodes. Then the member sensor nodes make local decision and each fusion node makes a final decision according to each member nodesimportance.

4. Voronoi diagram based node importance computing

4.1. Importance Degree

In blue-green algae surveillance, the green algae outbreak possibility differs in different water areas based on previous experience. There are many influencing factors, such as water temperature, weather conditions, and even geological terrain. Correspondingly, in order to assure timely outbreak prediction, more sensing resource should be allocated to water area wiht a high possibility of green algae outbreak .

In this paper, we divided the surveillance zone into a lot of discrete grids with their own impact factors. The importance degree of a grid is defined as the frequency of targets appearing in the grid, which is similar to [31]. We can get the grid's importance degree via a priori information. Besides, we also introduce the adaptive process of important degree to adjust the deviation, which is aroused by environment changes and wrong prior information. Different importance of the grids in the surveillance zone can be directly displayed by their different importance degrees. The higher the importance degree is, the higher the frequency targets appear, and the more importance the grid is. Consider the case where the surveillance zone D is a 2-Dimension region, then it can be divided into $m \times n$ grids $D = \{g_{ij}\}_{m\times n}$ and an importance degree matrix is defined as $A = [a_{ij}]_{m\times n}$, with a_{ij} representing the importance degree of grid g_{ij}. We assume that each grid is sensed with an exponentially distributed duration and it is generated via a probability density function $\zeta^{ij}(t) = a_{ij}e^{-a_{ij}t}$, where a_{ij} is the importance degree of the grid, t means the time duration and is set according to mission requirements. Next, in order to compute node importance, we need to introduce an definition about surveillance efficiency.

Surveillance efficiency: $\wp_{ij}(t)$, i and j represents a two-dimensional number of the grids, t represents the time scale. The surveillance efficiency concept can be understood like this: after the sensor detects a grid, the grid can be considered as fully understood; it goes down to zero. However, as time flows, the understanding of grids becomes more and more indistinct, while the surveillance efficiency increases until it returns back to zero. The higher the degree of importance of grid is, the more rapidly the detecting efficiency increases. The rate and accuracy of surveillance also get a corresponding increase. Then the surveillance efficiency function of grid g_{ij} at time t is computed by Eq. 1.

$$\wp_{ij}(t) = 1 - e^{-a_{ij}}[1 - \wp_{ij}(t-1)] \tag{1}$$

According to Eq. 1, at time t within a certain range, the larger a_{ij} is, the larger the value of $\wp_{ij}(t)$ is.

4.2. Node importance computing

First of all, the Voronoi diagram is utilized to define the effective scope of the sensor nodes. Suppose that $\Omega = \{n_1, n_2, ..., n_N\}$ is an aggregation of points in a two-dimensional Euclidean plane and these points are called sites. Because Voronoi diagram can decompose the space into regions around each site, the points in the grids around n_i are closer to n_i than any other point in Ω. According to [32], the Voronoi region $\Xi(n_i)$ for n_i can be described as follows.

$$\Xi(n_i) = \{x : d(n_i, x) \leq d(n_j, x), \forall j \neq i\} \tag{2}$$

where $\Xi(n_i)$ contains all points that are closer to the node n_i than any other site. The aggregation of all sites form the Voronoi Diagram $\Xi(\Omega)$. If there are denser sensor nodes in D, the Voronoi region acreage will be smaller because of large overlapped proportion.

In the paper, S-MAC protocol [33] is utilized for WSN communication. In this protocol, there includes two phases in each operation period (named Round) for sensor nodes. In the first phase, the node decides whether it should be awake or not stochastically via awakening probability. If it chooses awakening state, it will conduct detection or do some simple computation. Otherwise, it will just turn off to save energy. In the second phase, the sensor nodes make communication with their neighbors via receiving or sending information. The

Algorithm 1 2D-Voronoi mapping algorithm

Input: surveillance zone D, sensor nodes $\Omega = \{n_1, n_2, ..., n_N\}$

Output: Surveillance efficiency function $\wp_{ij}(t)$ and a mapping from 2-D dimension region to voronoi region $\Xi(n_i) \rightarrow \Gamma(n_i)$

Surveillance zone is divided into $m \times n$ grids $D = \{g_{ij}\}_{m\times n}$ and an importance degree matrix is defined as $A = [a_{ij}]_{m\times n}$, with a_{ij} representing the importance degree of grid g_{ij}.

for $i = 1$ to m **do**

  for $j = 1$ to n **do**

    The grid is sensed with an exponential distributed at time t computed by $\wp_{ij}(t) = a_{ij}e^{-a_{ij}t}$

    Compute surveillance efficiency of grid g_{ij} at time t: $\wp_{ij}(t) = 1 - e^{-a_{ij}}[1 - \wp_{ij}(t-1)]$

  end for

end for

for $k = 1$ to N **do**

  Compute the voronoi region of sensor node k : $\Xi(n_i) = \{x : d(n_i, x) \leq d(n_j, x), \forall j \neq i\}$

end for

for $k = 1$ to N **do**

  A mapping from $\Xi(n_i)$ to $\Gamma(n_i)$ is computed by $\{g_{ij} : g_{ij} \in \Xi(n_i)\}$

end for

return $\wp_{ij}(t)$ and $\Xi(n_i) \rightarrow \Gamma(n_i)$

sensor detection model can be defined as follows.

$$M(x, n_i) = \begin{cases} 1 & \{x : d(x, n_i) \le r, \forall x \in D\} \\ 0 & \{x : d(x, n_i) > r, \forall x \in D\} \end{cases} \quad (3)$$

where $d(x, n_i)$ means the distance between node n_i and geographical location point x.

Suppose there are sensor nodes $\Omega = (n_1, n_2, ..., n_N)$ and the Voronoi Diagram is $\Xi(\Omega) = \{\Xi(n_1), \Xi(n_2), ..., \Xi(n_N)\}$ where $\Xi(n_i)$ is the Voronoi region satisfying Eq. 2. Then a mapping from $\Xi(n_i)$ to $\Gamma(n_i)$ can be described as the following formula.

$$\Gamma(n_i) = \{g_{ij} : g_{ij} \in \Xi(n_i)\} \quad (4)$$

As shown in algorithm 1, the weight of the Voronoi region $\Xi(n_i)$ at time t $\omega(n, t)$ is defined as the sum of $\wp_x^{ij}(t)$ in the region D. Given $\wp_x^{ij}(t)$ and $\Gamma(n_i)$, $\omega(n_i, t)$ can be calculated by the following formula.

$$\omega(n_i, t) = \sum_{g_{ij} \in \Xi(n_i)} \wp^{ij}(t) \quad (5)$$

where $\omega(n_i, t)$ means the total amount of probability of the grids to be sensed. From Eq.(5), we can get the conclusion that numerous grids and high probability result in the large weight ω. Thus large $\omega(n_i, t)$ may indicate an urgent detection task on the node n_i. Then the importance degree of the effective scope may be computed via $\omega(n_i, t)$. Consequently, we construct the calculation about node importance as follows.

$$\eta(n_i, t) = \min\{C \times \omega(n_i, t) \times N/\Phi, 1\} \quad (6)$$

where N is the amount of sensor nodes in D, and Φ is the total amount of each grids max containing in D that can be computed by the following formula.

$$\Phi = \sum_{g_{ij} \in D} \max(\wp_{ij}(t)) \quad (7)$$

Besides, C denotes a variable parameter named perception factor, which makes the algorithm adaptive. Detailed explanations will be offered in section

8.2.5. The value of C is often selected by experimentation and experience and means the accuracy of the initial value of C, which may be a wrong choice. Thus we introduce an adaptive process of perception factor C to solve this problem. C can be computed as follows.

$$C = 10 \times \left(\frac{h}{N}\right)^4 \tag{8}$$

where h is the detected frequency within a period of t in one simulation, $C \in [0, 10]$. Obviously, the value of C will increases with the increase of a_{ij}. The dynamic change of C value can well avoid mistakes due to human factors, adapt to the effects of environmental changes, and response timely.

5. Forwarding costs based node importance computing

In real WSN-based applications, network topology often change dynamically. The sensor node with more forwarding choices often has more resilient to dynamic network environments. Instead of first making the forwarding decision and then waiting for the destination to wake up, opportunistic routing [34] means nodes forward packets opportunistically to their neighbors that wake first and provide enough route to the sink node. Therefore, the opportunistic routing is utilized to schedule the sleep time. Under such circumstance, one sensor node forwards a packet to its neighbor with respect to some metric, such as lower forwarding delays. When the sensor nodes are closer to the sink node that wake up more often, rendezvous with nodes closer to the sink becomes more efficient. The sensor nodes, which wake up more often than those farther away, are closer to the sink node [12]. In particular, energy budget is first fixted. If the desired network lifetime is given, it imposes a maximum duty cycle $\Im, 0 < \Im < 1$, that is equal for all the sensor nodes. The maximum fraction of time about the radio's status of each sensor node is decided by such maximum duty cycle. Because the radio of the sensor node is often the most power-hungry component, $\Im$ can guarantee the sensor nodes within a fixed energy budget. Then the awakening frequency needs to stay within the energy budget when the node importance is not considered. Given the forwarding delay $\Lambda(n_i, t)$ of the sensor node n_i , which is measured by each sensor node at runtime, a sensor node can computes its awakening frequency [12] without considering node importance as follows.

$$f_{no}(n_i, t) = \begin{cases} \infty & (if\ it\ is\ the\ always-on\ sink) \\ \frac{\Im}{\Lambda(n_i,t)} & \text{otherwise} \end{cases} \tag{9}$$

where $\Lambda(n_i)$ considers implementation-specific delays, such as packet retransmission and channel sensing. If $\Lambda(n_i)$ changes, the wake-up frequency of the sensor node will also be renewed. Because the sink node does not duty-cycle its radio, its direct neighbors within radio range undergo extremely short forwarding delays. Such delays equal to $\hbar$ analogously. Thus any node adapts its awakening frequency to $f_{no}(n_1) = \frac{\Im}{\hbar}$ when it is one hop neighbor of the sink node.

6. Intelligent awakening Scheme for information fusion

6.1. Intelligent awakening Scheme

Here we will propose the ESQG scheme (Energy-aware Scheduling with Quality Guarantee) for information fusion. This method calculates node awakening probability according to the different importance degrees of surveillance grids, residual energy of the sensor node and forwarding costs as shown in algorithm 2. To simplify the problem, we assume that all nodes have the same sensing range r and communication range.

In order to balance energy, we utilize the importance degree of the effective scope and the residual energy $\Re(n_i, t)$ to compute the sensor node importance. Thus the node importance is defined as follows.

$$\varphi(n_i, t) = \eta(n_i, t) \times \Re(n_i, t)/\Re^i_{init} \tag{10}$$

where $\Re_{init}$ is the initialization energy of the node n_i at time t, and residual energy of the node n_i is normalized by $\Re(n_i, t)/\Re^i_{init}$.

Algorithm 2 ESQG (Energy-aware Scheduling with Quality Guarantee)

1: $\wp_{ij}(t)$ and $\Gamma(n_i)$ is obtained by the Algorithm 1
2: **for** $k = 1$ to n **do**
3: The weight of Voronoi region $\Xi(n_i)$ at time t is calculated by $\omega(n_i, t) = \sum_{g_{ij} \in U(n_i)} \wp^{ij}(t)$
4: Compute the total amount of every grids max containing Φ in surveillance zone D by $\Phi = \sum_{g_{ij} \in D} \max(\wp_{ij}(t))$
5: Introduce an adaptive process of perception factor C which can be calculated by $C = 10 \times (\frac{n}{N})^4$, where n is the detected frequency within a period of t in one simulation, $C \in [0, 10]$.
6: **end for**
7: **for** $k = 1$ to N **do**
8: The node awakening probability may be calculated by $\eta(n_i) = \min\{C \times \omega(n_i) \times N/\Phi, 1\}$
9: The node importance computed by $\varphi(n, t) = \eta(n, t) \times \Re(n_i)/\Re^i_{init}$
10: Compute node waking frequency by $f(n_i, t) = \alpha \times f_{no}(n_i, t) + \beta \times \varphi(n_i, t)$.
11: The sensor node n_i can make a stochastic decision on switching from sleeping to activity according to $f(n_i)$. The higher the value of is, the more chance the node has got to be waken.
12: **end for**

Then the dynamic network topology and sensor node importance are considered comprehensively to computed the waking frequency as follows.

$$f(n_i, t) = \alpha \times f_{no}(n_i, t) + \beta \times \varphi(n_i, t) \quad (11)$$

where $\alpha + \beta = 1$. After the node awakening probability $f(n_i, t)$ is calculated, the sensor node can make a stochastic decision on switching from sleeping to activity accordingly. The higher the value of $f(n_i, t)$ is, the more chance the node has got to be waken. If a target is detected by an active node n_i, the nodes around it will be aroused. Otherwise they will return to sleep and set t to 0.

While the behavior of a single node (e.g., adjusting the wake-up frequency) is fairly easy to describe and understand, the emergent behavior of the system (e.g., the resulting activity gradient) is more complex and difficult to predict. To gain a further understanding about ESQG's gradient formation, we make a theoretical analysis. This analysis is not meant to define the assumptions or guidelines used for the practical implementation of ESQG, but to provide a clean setup for understanding ESQG's macro properties. A detailed description of ESQG's practical implementation is presented in Section 6.2.

6.2. Theoretical analysis

Because two hop neighbors of the sink can observe a higher forwarding delay than its one hop neighbors, their wake-up frequency can be adjusted accordingly. The process can be further spread accross the whole network, which will bring two important outcomes similar to [12]. a) end-to-end packet latency is significantly shorter, because it is decided by the sum of forwarding delays on all hops, which can be computed by formula $\Lambda(n_i) = \Lambda(\gamma, n_i) + \hbar$. b) duty cycle of the sensor node is decreased drastically, because less time and energy are spent to forward packets when the sensor nodes have the highest load. Note that nodes typically consume less energy than budget. This is because ESQG suppose there is always a packet to forward and awake frequency can be scheduled. Now one simple model is derived to understand how the gradients shape and steepness are controlled by the network topology, node importance , and energy budget.

If the forwarding delay at M hops from the sink is $H[\Lambda(M)] + \hbar$, their activity gradient can be computed as follows.

$$\begin{aligned} f(M,t) &\approx \frac{\Im}{\alpha \times (H[\Lambda(\gamma, M)] + \hbar) + \beta \times \varphi(n_i)} \\ &= \frac{\Im}{\alpha \times (1/(m+1)f(M-1,t) + \hbar) + \beta \times \varphi(n_i)} \end{aligned} \tag{12}$$

where $H[\Lambda(M)]$ is the expected value of the rendezvous time $\Lambda(\gamma, M)$. In the model, two assumptions are made: a) There are no collisions or message re-transmissions; b) all the sensor nodes with the same number of forwarders m. When all potential forwarders have the same wake up frequency f, an expected value of $\Lambda(M)$ can be computed by the following formula according to [35].

$$H[\Lambda(\gamma, n_i)] = \frac{1}{f(n_i,t) \times (m_{n_i} + 1)} \tag{13}$$

What is more, the formula mentioned above can be further simplified by setting $\hbar = 0$ for all the sensor nodes with $M > 1$, because there is often $\Lambda(M) \gg \hbar$ in such environment. Thus the simplified model can be described as follows.

$$\begin{aligned} f(M,t) &\approx \frac{\Im \times (m+1) f(M-1,t)}{\alpha + \beta \times \varphi(n_i,t)} \\ &= \frac{\Im \times (m+1)^{M-1} f(n_1,t)}{\alpha + \beta \times \varphi(n_i,t)} \end{aligned} \tag{14}$$

The activity gradient reaches the maximum frequency at one hop neighbors of the sink and decreases with geometric rate $\Im \times (M+1)$ similar to [12]. From the formula Eq. 14, we can show that the energy budget $\Im$ can be reduced in dense and wide networks when the number of forwarders raises, which does not affect the resulting activity gradient. Because an upper bound on the maximum energy usage is decided by the energy budget, the network lifetime can be extended when the energy budget $\Im$ is reduced.

7. Node importance based information fusion

On the basis of intelligent awakening scheme, the active sensor nodes are used to form cluster. Thus node importance based information fusion is proposed for target detection and the node importance is computed by considering both the importance of individual sensing scope and dynamic network topology which are discussed in the sec. 4 and sec. 5.

7.1. Sensor cluster formation

In the paper, a simple homogeneous model is utilized to covers a circular area with radius for each cluster [19], where S is the radius of the surveillance area and L_c is the number of clusters in the surveillance. Note that, in the considered model, there is a slight overlapping among adjacent clusters, which is due to the assumption of circular clusters. Hence, this model tends to slightly overestimate the average cluster size. Considering the number of nodes belonging to one cluster c_i, we make the assumption of uniform distribution of the nodes inside the clusters, i.e., a node belongs to a given cluster with probability $\frac{1}{L_c}$. In each cluster, the fusion node is selected according to the node importance. In particular, during the cluster formation process, the sensor node with the highest importance in one circular area is the fusion node and all the other sensor nodes in its circular area are member nodes.

7.2. Fusion rule

After the sensor node clusters have been formed to join in target detection, member sensor nodes first make local decision and transmit the local decision at each sample interval to the information fusion node in each cluster. Then each fusion node makes a final decision at each sample interval according to each member nodes importance as shown in Eq. (16).

$$\mho(c_k) = \sum_{n_i \in c_k} f(n_i, t) \times \digamma(n_i) \tag{15}$$

Where c_k is the number of k-th cluster in the monitoring area, $\mho(c_k)$ is the detection result of the cluster c_k, $\digamma(n_i)$ is the local decisions of the member nodes n_i in the cluster c_k . According to the discussion in the section 4 and 5, the dynamic network, residual energy and importance difference of the surveillance area are considered comprehensively to estimate the node importance (fusion weight). Thus, the information fusion performance can be improved efficiently to maintain high reliability while obtaining energy balance.

8. Experimental Analysis

In this section, detailed simulation results are provided to verify the effectiveness of our algorithm ESQG. In particular, the simulation time, energy saving result, failure time and the parameter choice of perception factor C are evaluated.

8.1. Simulation Environment

In the simulation, there is 100×100 blue-green algae surveillance zone, which is divided into a lot of discrete grids with 2.5×2.5. 100 sensor nodes are scattered randomly in the zone, and the location of sensor node can be obtained either via hardware such as embedded GPS or location algorithms [36]. We also suppose that the sensor node's radio communication radius satisfies the critical density conditions [37] at all times. This indicates the network is always connected. Thus the desired area to monitor of a sensor node is the polygon defined by the Voronoi diagram. Besides, we set the energy budget $\Im$ to 8% and set the sensing range in Eq. 3 to 20. As Fig. 2 shows, because of random configuration in real surveillance, the sensor nodes are unevenly distributed.

Furthermore, proper importance degrees have been assigned to the discrete grids before WSN deployment via temperature, weather conditions and geological terrain. Thus high important degree are usually assigned to the grid wiht high outbreak possibility. Because the whole surveillance zone is defined as D, the sink and different importance degrees of the grids in D are showed in Fig. 3. Besides, the importance locations are also figured as the green pentagram called G such as a road or a battlefield etc. We assume the sensing task requires

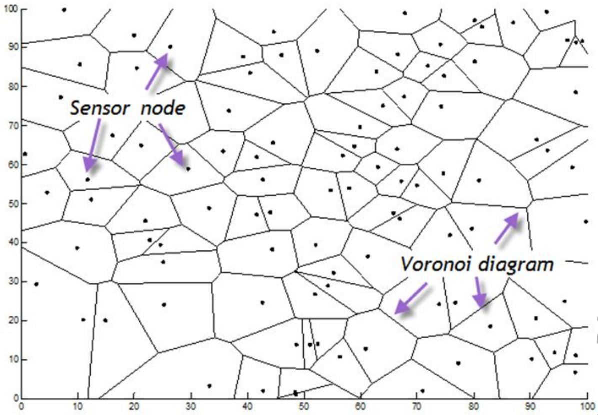

Figure 2: The sensor nodes and its Voronoi diagram

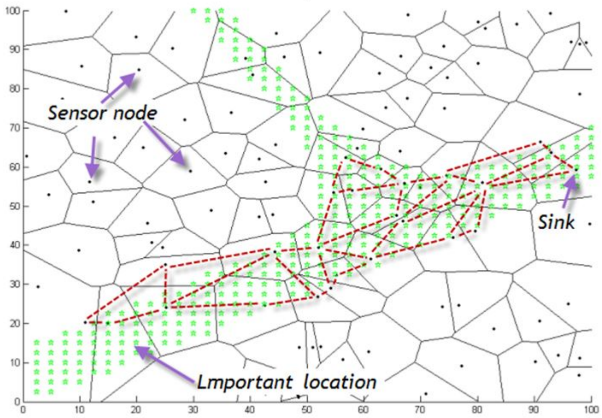

Figure 3: The importance location figured as the area with green pentagram

the grids in G to be detected in $t_1 = 2.5$ second interval while the other grids to be detected in $t_2 = 5$ second interval. Then the importance degree of the grid a_{ij} can be computed by the following formula.

$$a_{ij} = \begin{cases} 1/t_1 & g_{ij} \in G \\ 1/t_2 & g_{ij} \in D - G \end{cases} \tag{16}$$

What is more, the corresponding grids set $\Gamma(n_i)$ can be calculated according to Eq. 4 when the sensor node n_i and grid g_{ij} are given. $\wp^{ij}(t)$ and $\omega(n_i, t)$ can

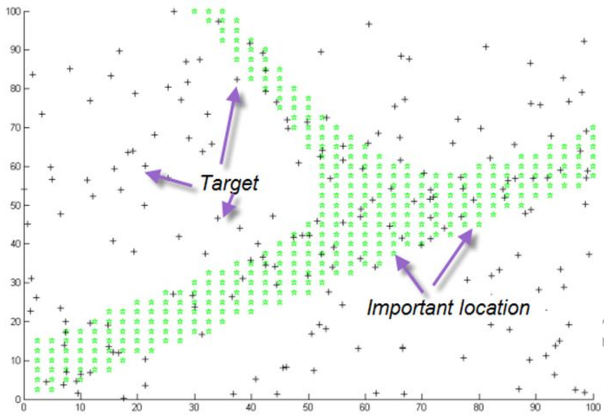

Figure 4: Targets appearing in the surveillance zone

be computed via Eq. 1 and Eq. 5 respectively. According to Eq. 9, we can also compute the sensor nodes' awakening probability. In order to evaluate ESQG in a dense targets environment, we generate the mornitoring targetsrandomly with the number $K = \{50, 100, 150, 200\}$ respectively and green algae means outbreak event. The probability targets appearing in G is twice of that in the other location. As shown in Fig. 4, there is a snapshot of 200 targets, which are generated in our simulation experiment.

In order to verify the effectiveness of our approach ESQG, we also selected four contrasting methods, named: `ConstP`, `Staffetta`, `WakeE` and `ALLe` respectively. ConstP method [24]: it uses fixed awakening probability p evaluated in the interval [0,1]. While the perception factor C in ESQG is evaluated in the interval [0,10]. `Staffetta` [12]: it can dynamically adapt each node's wake-up frequency to its current forwarding cost, so nodes closer to the sink become more active than nodes farther away. `WakeE` method [29]: the sensor nodes are organized into cluster and set their states into sleep/active mode based on their residual energies in each cluster. `ALLe` method: It makes all the sensors join in the target detection and all the sensor nodes are always active. Besides, ESQG scheme without energy balance strategy is called ESQGn method, which can verify sensing performance of ESQG.

In order to evaluate the performance of our method, we define metrics as follows. *Simulation time*: it demonstrates the agility of the system to targets. *Energy*: it is defined as the accumulated times of awakening nodes during one simulation. *Number of failed simulations*: it is accumulated to reflect the robustness of the algorithm in the experiment. *Lifetime*: it is the time when the energy of the first node is depletion in WSNs. Lifetime is the metrics of energy balance. *Standard deviation of residual energy*: It reflects the discrete degree of residual energy of the nodes in networks, and it is another metric of energy balance among nodes. *False positive rate*: It is calculated as the ratio between the number of negative events wrongly categorized as positive (false positives) and the total number of actual negative events. *False negative rate*: It is calculated as the ratio between the number of positive events wrongly categorized as negative (false negatives) and the total number of actual positive events. The false positive rate and false negative rate are used to measure the performance of our proposed information fusion scheme.

In the simulation experiments, the system is initialize by setting the time $t_0 = 0$. Every grid is set to activity via the sensor node's awakening probability. At time $t_0 + 1$, K random targets occur in the surveillance area. When all the targets are detected the simulation is demonstrated successful and the simulation time t is recorded. If there are still targets that fail to be detected by the time $t_0 + 5$, then the simulation is demonstrated as a failure. Besides, the number of the simulations is set to 30 in the simulation. Let simulation time and energy usage be the mean value of 30 simulations respectively and the number of failure simulations be the times of failed simulations in the experiment.

8.2. Experimental results Analysis

Because only our method and `ConstP` have perception factor C or p, we first make comparison simulation time, energy consumption and failure time of [13] with that of `ConstP` method under different C or p. Then, We make comparison simulation time, energy consumption and failure time of ESQG and ESQGn with that of `ConstP`, `Staffetta`, `WakeE` and `ALLe` method under different number of targets. Thirdly, the Standard deviation of residual energy and lifetime about ESQG and ESQGn methods are compared with that of `ConstP`, `Staffetta`, `WakeE` and `ALLe` method. Besides, the false negative rate and false negative rate are compared. Finally, the performance of self-adaption of perception factor is discussed.

8.2.1. Comparison with different parameter C or p

The simulation time, energy cost and failure time of [13] and `ConstP` method under different C or p are shown in Fig. 5 and 6. Fig. 5(a) and Fig. 6(a) show that simulation time is attenuating with the increase of perception factor C and probability p. When $C \geq 2$ and $p \geq 0.9$, simulation time remains stable at the value of 6, which means the targets can be detected as soon as they are generated. C indirectly reflects the degree of importance of this simulation time, which plays a very important role in the simulation. Fig. 5(b) and Fig. 6(b) illustrate that energy usage increases monotonously with perception factor and probability p. Compared to `ConstP` method, the energy cost of ESQG is robust to different targets number K. From Fig. 5 (a-b) and Fig. 6 (a-b), we can also observe that `ConstP` method usually costs more energy than ESQG with the same simulation time. Fig. 5 (c) and Fig. 6 (c) show the relationship of the failure times with perception factor C and p when different targets numbers are applied. These figures indicate that failure time increases when either parameter C or p decreases. Meanwhile, its clear that with respect to `ConstP` method, failure times in ESQG are less affected by the targets number K, which implies the superior robustness of ESQG.

From the simulation results mentioned above, we can show that the energy usage is reduced by the decrease of C and p. Besides, the failure times will increase if the parameter C or p decreases. The simulation time and energy usage will increase through adding targets number K. Thereby, it is vital to reasonably choose the parameters C according to different applications in order to ensure the optimizing performance of the system. For the importance of C, we make a further analysis on the perception factor C.

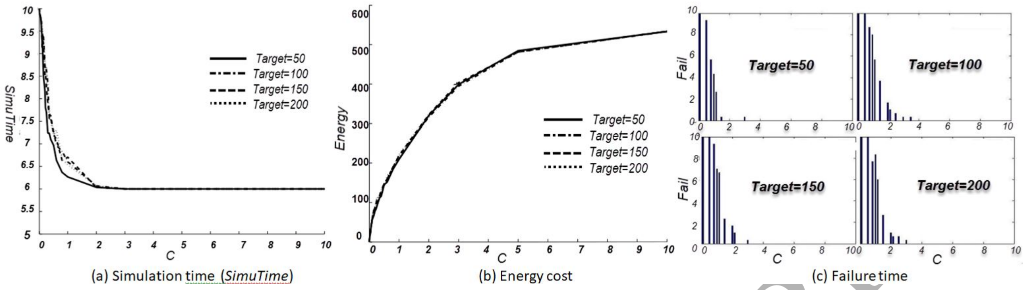

Figure 5: Simulation time, Energy cost and Failure time with different target numbers of [13] under different C

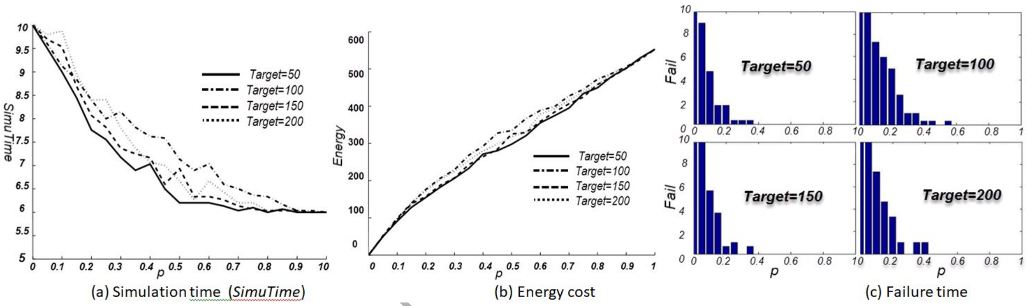

Figure 6: Simulation time, Energy cost and Failure time with different target numbers of ConstP under different p

8.2.2. Comparison with different number of target (TarN)

We compare our method ESQG and ESQGn with `ConstP`, `Staffetta`, `WakeE` and `ALLe` method about simulation time, energy consumption and failure time under different number of targets (TarN=50, TarN=100, TarN=150, TarN=200). Because simulation time remains stable at the value of 6 according to the analysis of Section 8.1, if $C \geq 2$ and $p \geq 0.9$, the parameter C in our algorithm is set to 2 and the parameter p in `ConstP` method is set to 0.9. As shown in Fig. 7, simulation time of ESQG and ESQGn is lower than that of `WakeE` method. That is because ESQG and ESQGn considers importance degree of the effective scope to compute sensor nodes awakening probability, which directly reflects the

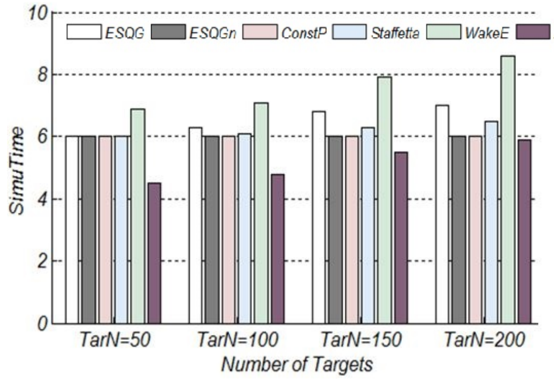

Figure 7: Simulation time with different TarN

nodes sensing capability. While `WakeE` only considers nodes residual energy to wake up sensor nodes. Besides, simulation time of ESQGn is the same to that of `ConstP` method for $C = 2$ and $p = 0.9$. Fig. 8 shows that the energy consumption of ESQG is less than that of ESQGn, ConstP, Staffetta, WakeE and ALLe methods with different number of targets (TarN=50, TarN=100, TarN=150, TarN=200) for importance degree, residual energy and dynamic network topology are both considered in ESQG, while ESQGn and `ConstP` method without energy balance scheme. Because `WakeE` only utilizes sensor nodes residual energy to wake up sensor nodes and can not selects the most important nodes, it will wake up more sensor nodes than that of ESQG. As shown in Fig. 9, the number of failure time of ESQG and ESQGn is lower than that of `ConstP` and `WakeE` method. That is because ESQG and ESQGn considers importance degree of the effective scope to compute nodes awakening probability.

8.2.3. Comparison about energy balance

In this section, we make comparison our methods lifetime and standard deviation of sensor nodes residual energy with that of `ConstP`, `Staffetta`, `WakeE` and `ALLe` method under different number of target (TarN=50, TarN=100, TarN=150). We assume the initial energy of each node is 20J. As shown in Fig. 10, 13 and 14, the standard deviation of residual energy for ESQGn, `Staffetta`,

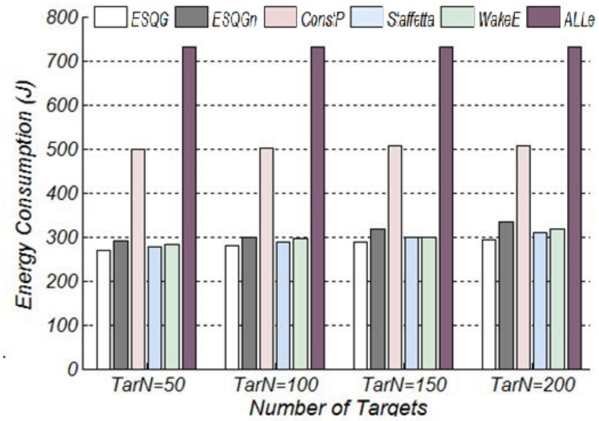

Figure 8: Energy consumption with different TarN

ConstP and WakeE at different TarN is bigger than that of ESQG and ALLe. Thats because ALLe make all the sensor nodes active during each iterations and ESQG has energy balance mechanism. Fig. 15 shows that the lifetime of ESQG is longer than that of other methods for importance degree and residual energy are both considered in ESQG, while ESQGn and ConstP method without energy balance scheme. Because WakeE only utilizes sensor nodes residual energy to wake up sensor nodes and can not selects the most important nodes, it will wake up more sensor nodes than ESQG. Besides, with increase of TarN, the lifetime of ESQG decrease for the number of active nodes increase. Because ESQGn and ALLe do not have energy balance schemes and select the most important sensor node during each round, they always use the same nodes and their lifetime is the same.

From simulation results we can show that ESQG is superior to other four methods in performance. The main reason is that ESQG not only consider the dynamic network topology and the residual energy of the sensor node but also utilizes importance degree based scheduling scheme to raise efficiency.

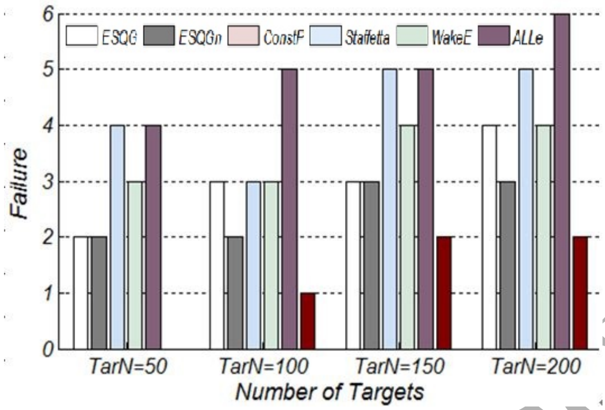

Figure 9: Failure time with different TarN

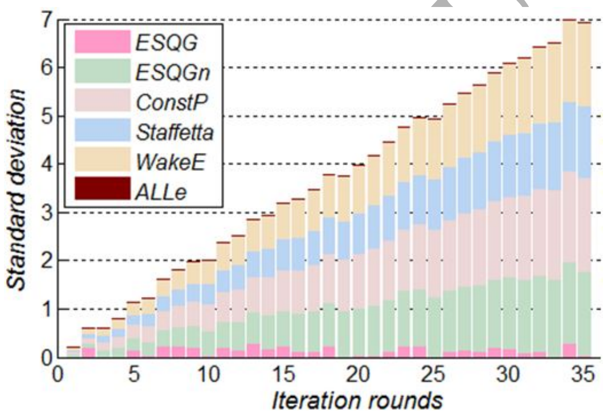

Figure 10: Standard deviation of the residual energy when TarN=50

8.2.4. False positive rate and false negative rate

In this section, in order to evaluate the performance of our information fusion scheme, we will make comparison our method with traditional methods including ConstP, Staffetta, WakeE and ALLe about false positive rate and false negative rate. As shown in Fig. 11, because ESQG and ESQGn consider the dynamic network and importance difference of the surveillance area comprehensively, they have lower false positive rate than that of other traditional methods. While because ESQGn has energy balance scheme, it does not con-

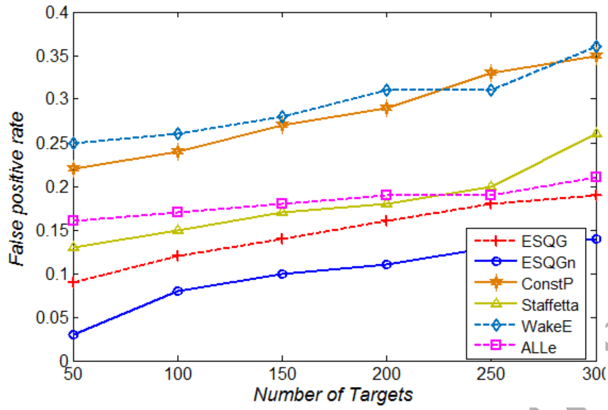

Figure 11: False positive rate

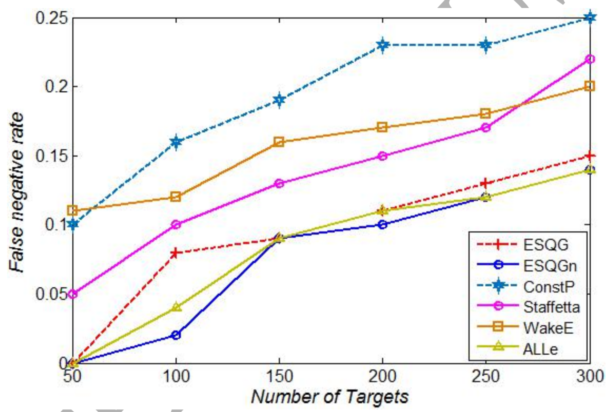

Figure 12: False negative rate

sider the real fusion weight of the sensor node than that of ESQG. Thus its has lower higher false positive rate than that of ESQG. Because ConstP method does not consider the difference of sensor nodes fusion weight, which are the same for different sensor nodes, it has higher false positive rate than that of other methods. Besides, although ALLe also has the same fusion weight for different sensor nodes, it has lower false positive rate than that of ConstP, Staffetta, and WakeE method, that is because all the sensor node are active for ALLe method and get more information about the target.

Similarly, as shown in Fig.12, ESQG and ESQGn have lower false negative rate than that of ConstP, Staffetta and WakeE methods which do not consider the effect on information fusion weight about the dynamic network and importance difference of the surveillance area. While because ConstP method does not consider the difference of sensor nodes fusion weight, which are the same for different sensor nodes, it has higher false negative rate than that of other methods.

8.2.5. Self-adaption of perception factor

As what has been mentioned above, Fig. 5(a) and 5(b) show that C value determines the accuracy of the algorithm (ESQG) to a great extent. C was set to a definite value in above simulation, but in practical use, it is not accurate. The main reasons are as follows: firstly, the perception factor value should be changing with the change of external environment. Set Blue-green Algae Bloom on Lake Tai as an example: when the algae from the quiet period into algae bloom period, the perception factor value should have a certain change. Secondly, the initial value of C may not set correctly. Usually C is the parameter chosen by experimentation and experience, which means the accuracy of the initial value of C may be a wrong choice. So we introduce an adaptive process of perception factor C which can be calculated by Eq. 8. C firstly is the parameter chosen by experimentation and experience, then start to carry out self-adaption to match the actual situation, and automatically change according to the detected data. Dynamic change of C value can well avoid mistakes due to human factors, adapt to effects of environmental changes, and response timely.

New Simulation Environment In order to simplify the simulation, we change the environment as follows in Fig. 16. The content in the Fig. 16 is similar to the one in Fig. 4, such as the target number, the Voronoi model, except for the importance location. We change the importance location to simulate possible changes in reality and to test whether the perception factor C can provide appropriate adaptive process to the algorithm. The probability targets appearing in G (the importance location) is also twice of that in the other location, and have 200 targets generated in our simulation.

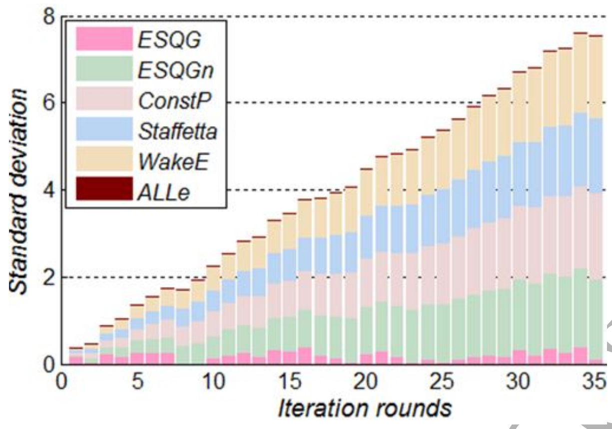

Figure 13: Standard deviation of the residual energy when TarN=100

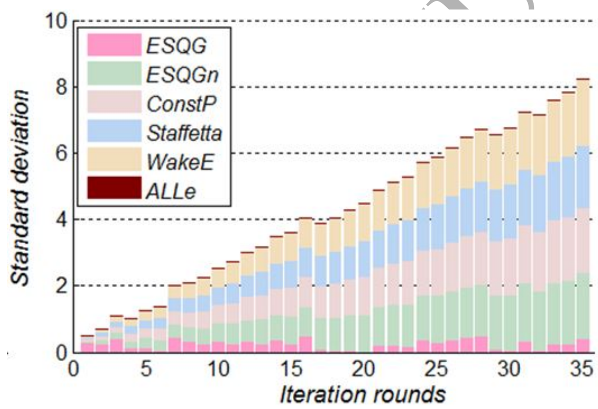

Figure 14: Standard deviation of the residual energy when TarN=150

The initial setup of C value in the simulation is 1.8. We use the first simulation environment (Fig. 4) before seventh simulation time, and after that, we start using the new one (Fig. 16) to observe the changing process of perception factor C and test the stability of the system.

Results Analysis We draw a curve graph to record C changing process between the two simulations for better observation: According to Fig. 17, the initial value of C is 1.8, which is obviously a wrong estimation. In the first scenario, test point is located in the non-key area, whose C value is about 0.23

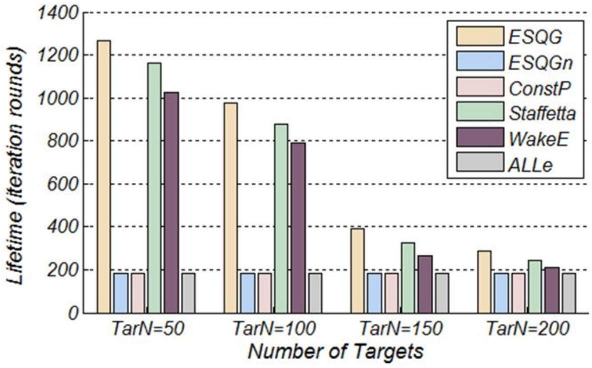

Figure 15: Lifetime (iteration rounds) in different TarN

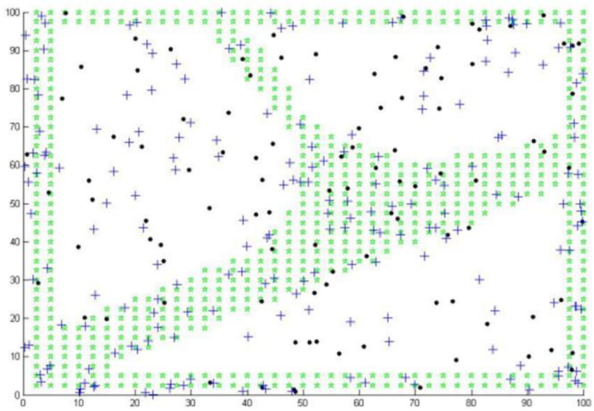

Figure 16: New targets appearing in the surveillance zone

which can be calculated with Eq. 9. While in the seventh simulation, we changed the scene into Fig. 16, where the test point is exactly located in the key area, and the C value increased to 0.46, which showed a good self-adaptive function of ESQG. Meanwhile, with the self-adaption of C, the algorithm can avoid the errors brought by environmental changes and human factors, and correct the initial value error and adapt to environmental changes.

From simulation results above we can draw the following conclusions: Adaptive perception factor C method can be well matched with ESQG. It solves problems caused by experience evaluation and gives C a chance for correction.

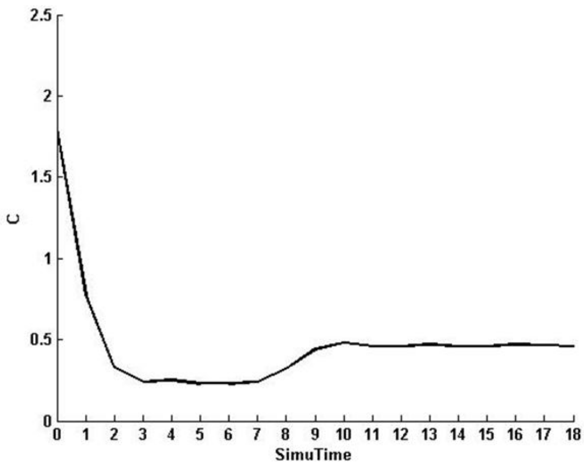

Figure 17: The adaptive process of value C

And it can let ESQG flexibly adapt to the environmental change. However, a compromise is time sacrifice. It needs to sacrifice some delay time to ensure self-adaption, and analyze the results, then make responses after one entire detection. But compared with the environmental change time, this delay time is quite short, therefore it just has little influence on the overall function.

9. Conclusions

In this paper, we propose the ESQG scheme for information fusion to save network resources through considering dynamic network topology and different importance degrees of blue-green algae surveillance locations. In the scheme, importance degree is introduced to reflect the different importance of the grids in the surveillance zone. Combined with the difference of surveillance zones importance degree and dynamic network topology, it is used to calculate the awakening probability which determines the modes of the sensor nodes. Then node importance based Information fusion is conducted to improve target detection performance. Besides, an adaptive process of perception factor C is proposed to match actual situation, and automatically change according to the detected data. Thus a compromise is achieved between energy cost and system agility. Our conducted green algae surveillance simulation results show that our approach is robust and energy-efficient. Simulation results also suggest that this scheme can reduce the number of awakening nodes to a large extent while maintaining high reliability in surveillance.

Acknowledgement

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References

References

[1] K. Xiao, R. Wang, T. Fu, J. Li, P. Deng, Divide-and-conquer architecture based collaborative sensing for target monitoring in wireless sensor networks, Information Fusion 36 (2017) 162–171.

[2] K. Xiao, R. Wang, L. Zhang, J. Li, T. Fun, Asmt: An augmented state-based multi-target tracking algorithm in wireless sensor networks, International Journal of Distributed Sensor Networks 13 (4) (2017) 1–9.

[3] S. Rodrguez, J. F. D. Paz, G. Villarrubia, C. Zato, J. Bajo, J. M. Corchado, Multi-agent information fusion system to manage data from a wsn in a residential home, Information Fusion 23 (C) (2015) 43–57.

[4] D. Li, Z. Zhao, L. Cui, H. Zhu, L. Zhang, Z. Zhang, Y. Wang, H. M. Chen, The design and implementation of a surveillance and self-driven cleanup system for blue-green algae blooms on lake tai (2010) 759–761.

[5] G. Jaber, R. Kacimi, Z. Mammeri, Exploiting redundancy for energy-efficiency in wireless sensor networks, in: Wireless and Mobile NETWORKING Conference, 2016, pp. 180–186.

[6] F. Song, B. Yang, Y. Zhao, A novel sleeping scheduling method for wireless sensor networks based on data fusion, International Journal of Future Generation Communication and Networking 9 (2) (2016) 155–162.

[7] N. Lavanya, T. Shankar, A review on energy-efficient scheduling mechanisms in wireless sensor networks, Indian Journal of Science and Technology 9 (32).

[8] F. L. Lewis, Wireless sensor networks, Smart Environments Technologies Protocols and Applications 181 (1) (2004) 11–46.

[9] O. Landsiedel, E. Ghadimi, S. Duquennoy, M. Johansson, Low power, low delay: Opportunistic routing meets duty cycling, in: ACM/IEEE International Conference on Information Processing in Sensor Networks, 2012, pp. 185–196.

[10] J. Kim, X. Lin, N. B. Shroff, Optimal anycast technique for delay-sensitive energy-constrained asynchronous sensor networks, IEEE/ACM Transactions on Networking 19 (2) (2011) 484–497.

[11] M. Zimmerling, F. Ferrari, L. Mottola, T. Voigt, L. Thiele, ptunes: runtime parameter adaptation for low-power mac protocols, in: International Conference on Information Processing in Sensor Networks, 2012, pp. 173–184.

[12] M. Cattani, A. Loukas, M. Zimmerling, M. Zuniga, K. Langendoen, Staffetta: Smart duty-cycling for opportunistic data collection, in: ACM Conference on Embedded Network Sensor Systems Cd-Rom, 2016, pp. 56–69.

[13] R. Wang, L. Zhang, L. Cui, Intelligent wakening scheme for wireless sensor networks surveillance, in: Computer Communications Workshops, 2011, pp. 744–749.

[14] X. Zhao, Q. Luo, B. Han, Survey on robot multi-sensor information fusion technology, in: Intelligent Control and Automation, 2008. Wcica 2008. World Congress on, 2008, pp. 5019–5023.

[15] T. Ma, Y. Liu, J. Fu, Y. Jing, A reliable information fusion algorithm for reputation based wireless sensor networks, International Journal of Future Generation Communication and Networking 8 (1) (2015) 114–118.

[16] L. Snidaro, J. Garca, J. Llinas, Context-based information fusion: A survey and discussion, Information Fusion 25 (2015) 16–31.

[17] J. A. Balazs, Opinion mining and information fusion, Information Fusion 27 (C) (2016) 95–110.

[18] U. M?nks, H. Trsek, L. Drkop, V. Genei?, V. Lohweg, Towards distributed intelligent sensor and information fusion, Mechatronics 34 (2015) 63–71.

[19] A. Abrardo, M. Martal, G. Ferrari, Information fusion for efficient target detection in large-scale surveillance wireless sensor networks, Information Fusion 38 (2017) 55–64.

[20] Z. X. Liu, C. X. Xie, M. Xie, J. Mao, Mobile robot positioning method based on multi-sensor information fusion laser slam, Cluster Computing (84) (2018) 1–7.

[21] P. Wei, J. E. Ball, D. T. Anderson, Multi-sensor conflict measurement and information fusion, in: Signal Processing, Sensor/Information Fusion, and Target Recognition XXV, 2016.

[22] K. Xiao, J. Li, C. Yang, Exploiting correlation for confident sensing in fusion-based wireless sensor networks, IEEE Transactions on Industrial Electronics 65 (6) (2018) 4962–4972.

[23] R. C. Carrano, D. Passos, L. C. S. Magalhaes, C. V. N. Albuquerque, Survey and taxonomy of duty cycling mechanisms in wireless sensor networks, IEEE Communications Surveys and Tutorials 16 (1) (2014) 181–194.

[24] R. D. P. Alberola, D. Pesch, Duty cycle learning algorithm (dcla) for ieee 802.15.4 beacon-enabled wireless sensor networks, Ad Hoc Networks 10 (4) (2012) 664–679.

[25] J. He, L. Duan, F. Hou, P. Cheng, J. Chen, Multiperiod scheduling for wireless sensor networks: A distributed consensus approach, IEEE Transactions on Signal Processing 63 (7) (2015) 1651–1663.

[26] D. Ye, M. Zhang, A self-adaptive sleep/wake-up scheduling approach for wireless sensor networks, IEEE Transactions on Cybernetics PP (99) (2017) 1–14.

[27] L. Rajesh, C. R. B. Reddy, Efficient wireless sensor network using nodes sleep/active strategy, in: International Conference on Inventive Computation Technologies, 2017, pp. 1–4.

[28] B. Zhang, E. Tong, J. Hao, W. Niu, G. Li, Energy efficient sleep schedule with service coverage guarantee in wireless sensor networks, Journal of Network and Systems Management 24 (4) (2016) 834–858.

[29] K. Sundaran, V. Ganapathy, Energy efficient wireless sensor networks using dual cluster head with sleep/active mechanism, Indian Journal of Science and Technology 9 (41).

[30] C. Zhang, S. Wan, Z. Yao, B. Zhang, C. Li, A distributed battery recovery aware topology control algorithm for wireless sensor networks, Wireless Communications and Mobile Computing 16 (17) (2016) 2895–2906.

[31] H. Moravec, Certainty grids for mobile robots, 1987, pp. 61–74.

[32] L. J. Larsson, R. Choksi, J. C. Nave, Geometric self-assembly of rigid shapes: A simple voronoi approach, Siam Journal on Applied Mathematics 76 (3) (2016) 1101–1125.

[33] W. Ye, J. Heidemann, D. Estrin, An energy-efficient mac protocol for wireless sensor networks, in: IEEE Global Telecommunications Conference, 2002, pp. 1567–1576 vol.3.

[34] R. W. L. Coutinho, A. Boukerche, L. F. M. Vieira, A. A. F. Loureiro, Geographic and opportunistic routing for underwater sensor networks, IEEE Transactions on Computers 65 (2) (2016) 548–561.

[35] E. Ghadimi, O. Landsiedel, P. Soldati, S. Duquennoy, M. Johansson, Opportunistic routing in low duty-cycle wireless sensor networks, Acm Transactions on Sensor Networks 10 (4) (2014) 1–39.

[36] A. Cenedese, G. Ortolan, M. Bertinato, Low-density wireless sensor networks for localization and tracking in critical environments, IEEE Transactions on Vehicular Technology 59 (6) (2010) 2951–2962.

[37] S. Adlakha, M. Srivastava, Critical density thresholds for coverage in wireless sensor networks, in: Wireless Communications and Networking, 2003. WCNC 2003, 2003, pp. 1615–1620 vol.3.