EEGRA: Energy Efficient Geographic Routing Algorithms for Wireless Sensor Network

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ABSTRACT

Energy efficiency is critical in wireless sensor networks (WSN) for system reliability and deployment cost. The power consumption of the communication in multi-hop WSN is primarily decided by three factors: routing distance, signal interference, and computation cost of routing. Several routing algorithms designed for energy efficiency or interference avoidance had been proposed. However, they are either too complex to be useful in practices or specialized for certain WSN architectures. In this paper, we propose two energy efficient geographic routing algorithms (EEGRA) for wireless sensor networks, which are based on existing geographic routing algorithms and take all three factors into account. The first algorithm combines the interference into the routing cost function, and uses it in the routing decision. The second algorithm transforms the problem into a constrained optimization problem, and solves it by searching the optimal discretized interference level. We integrate four geographic routing algorithms: GOAFR+, Face Routing, GPSR, and RandHT, to both EEGRA algorithms and compare them with three other routing methods in terms of power consumption and computation cost for the grid and irregular sensor topologies. The results of our experiments show both algorithms conserve sensor's routing energy 30% ~ 50% comparing to general geographic routing algorithms. In addition, the time complexity of EEGRA algorithms is similar to the geographic greedy routing methods, which is much faster than the optimal SINR-based algorithm.

Keywords
Geographic routing; Energy-efficiency; Wireless sensor network; SINR; Distributed routing algorithm

1. INTRODUCTION

The research of the wireless sensor networks (WSN) has garnered increasing attention owing to its technical importance in widespread applications, such as monitoring and surveillance in the military, civil industries, home automation and traffic control fields. In general, the communication method used in WSN is multi-hopping, by which messages are transmitted through a sequence of sensor nodes (SN).

Two critical issues in the multi-hop WSN are routing and power consumption. Routing is the process of forwarding messages from a source node to a destination node in a communication network. Routing in WSN is notably different from that in wired networks. First, in WSN, each node is assumed to work as a router that helps forward a message on its way to the destination node. A sensor node has finite storage and limited computational power. Second, in nature, wireless connections are less stable than wired networks because the wireless network is prone to radio signals attenuation, signal interference, and signal noises. Wireless routing algorithms should account for some potential factors such as signal disturbances and other dynamic characteristics.

Another critical issue in the WSN is the power control since sensor nodes have limited power capacities. For multi-hop WSN, the power consumption of communication is primarily decided by three factors: routing distance, signal interference, and computation cost of routing. The relations of power consumption and the routine distance can be simply reasoned: the longer routing distance, the larger power consumption. Similarly, the more complicated computation requires more power. The relation of power consumption and signal interference can be explained by the SINR model [1]. In general, to keep the same communication quality, the stronger signal interference implies the more power consumption.

The problem of energy efficient routing is to find a multi-hop path for a given source and destination, along which the power consumption is minimized. People had proposed different methods for energy efficient routing based on interference avoidance. First, communication that utilizes multi-channel capacity to reduce the signal interference was proposed in [4]. Nevertheless, this only applicable to the network supporting multi-channel and cannot be scalable well. Interference might still be generated if many communicated tasks transmit in the same channel. Second, algorithms using scheduling, which can be regarded as another type of multi-channel method (time division), to avoid the transmission of nearby SNs had been studied in [2][3]. However, the scheduling needs to keep a lot of information such as sensor's time slots and neighbor's affection. It is not a dynamic method and not appropriate to practical WSNs environment. Third, in [5], the I2MR algorithm is proposed, in which the interference is characterized using the discrete graph model and avoided by cutting the adjacent edges of communicating SNs. Because of the removal of usable links, the transmission can be blocked. Last, in [6], Kwon and Shroff transformed the SINR to power consumption, and employed the shortest path algorithm to search the route with minimum energy cost. The method minimizes energy consumption in WSNs that guarantees transmission quality, but the time complexity of routing calculation, solving the shortest path problem, is too high.

In this paper, we propose two energy efficient geographic routing algorithms. They are based on geographic routing algorithms [7][8][9][10], because their low computation and storage requirements fit the WSN environments. The interference model used in the algorithms follows the approach proposed in [6], which measures the power consumption by signal-to-interference-and-noise (SINR). We implemented our algorithms by integrating several geometric routing algorithms, and the results show they can reduce power consumption up to 50%, comparing to general geographic routing algorithms without any energy awareness. In addition, the time complexity of our algorithms is similar to the geographic routing algorithms, which is much faster than the existing optimal SINR-based algorithm. Moreover, we compared our algorithms with the I2MR algorithm, and measured routability by the number of available paths. The result indicates that our methods have much better routability than the I2MR algorithm.

The rest of this paper is organized as follows. In section 2, we provide the background of the problem and algorithms, including problem formulation and related works. In section 3, we introduce the used interference model and a practical computational method for it. In section 4, we present our energy efficient routing algorithms with analysis. In section 5, the experimental setting and results are illustrated. The conclusion and future work are given in section 6.

2. Background

In this section, we introduce our problem formulation, the theoretical power model, and related work.

2.1 Problem formulation

A WSN is modeled as a graph, $G(V,E)$, in which $V=\{v_1, v_2,\ldots, v_n\}$ is the set of sensor nodes and $E=\{e_1,e_2,\ldots,e_m\}$ is the set of transmission edges. Every transmission edge e_i is defined by two sensor nodes (T_{e_m}, R_{e_i}) if they are in each other's communication range. More precisely, two nodes are commutable directly if each can receive other's signal with strength larger than some threshold δ_A. The signal strength is measured by SINR, which implies that when there are interferences, stronger signals need be emitted to maintain the same SINR. We assume each SN can adjust their power to meet the required signal strength upon some limits.

The problem is to find a route of a given pair of the source node (s) and the destination node (d) such that the energy consumption is minimized. The problem formulation is given in (1), which minimizes the total energy consumption of a multi-hop message transmission,

$$\arg\min_{R(s,d)\subseteq E} \sum_{e_i\in R(s,d)} \Delta p\left(T_{e_i}\right) \qquad (1)$$
$$\text{subject to } \ \theta(e_i) \geq \theta_0$$

where $R(s, d)$ is a route from the source node s to the destination node d, $\Delta p\left(T_{e_i}\right)$ the power consumed by transmitter node T_{e_i} for each edge e_i on the route R, $\theta(e_i)$ is the signal strength (SINR) of edge e_i, and θ_0 is the required SINR. This formulation is the same as the one defined in [6]. The relation of $p(e_i)$ and $\theta(e_i)$ will be explained in Section 2.2.

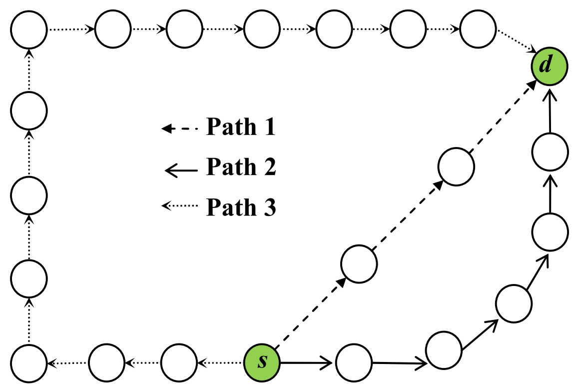

Figure 1. Three paths from node *s* to node *d*.

There are three factors to influence the power consumption. First, the routing distance from node s to node d. However, the shortest one may not be the best. Figure 1 shows an example, which has three paths from s to d. Path 1 (dashed lines) is the shortest, but the distance of each hop is double of that of Path 2 (solid lines). Because the power consumption is proportional to the square of distance for the same signal strength [1][11], the power consumption of Path 1 is actually double comparing to that of Path 2, although the number of hops of Path 2 is twice as many as those of Path 1. The hop distance of Path 3 is slightly shorter than that of Path 2, but its number of hops is much more than that of Path 2. Therefore, the path with minimum power consumption is Path 2.

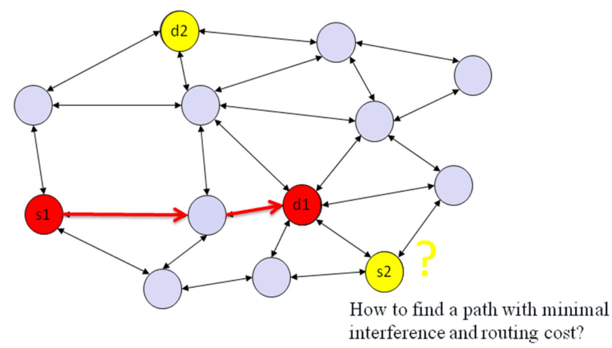

Figure 2. An example of multiple transmissions

The second factor is the interference caused by other transmission. Figure 2 shows an example that a new pair transmission (s_2, d_2) is about to start while there exist another ongoing transmission (s_1, d_1). In this case, the shortest path between (s_2, d_2) may not be the route of minimum power consumption because extra power needs to pay to maintain the same signal strength.

The last factor is the power consumption spent on the computation of the route. Complicated computations, although may find a better route, can exhaust the power of sensor node quickly. In this paper, we did not use any power model to measure the power consumption of computation. A separated evaluation of computational cost will be used in comparison.

2.2 The theoretical power model

We use signal-interference-noise ratio (SINR), which measures the ratio of transmission signal strength to the interference and noise, in our power model because it considers the power spent on message transmission and interference together. For a transmission edge e_i, the sum of noise and interference at the receiver node R_{e_i} can be expressed by the following equation,

$$I_{f(e_i)} = \sum_{\mathrm{m:m\neq i}} G(T_{e_m}, R_{e_i}) p(T_{e_m}) + \eta_i \qquad (2)$$

in which $G(T_{e_m}, R_{e_i})$ is the path gain between T_{e_m}: the transmitter on edge e_m, and R_{e_i}: the receiver on link e_i; $p(T_{e_m})$ is the transmission power of transmission nodes T_{e_m}; and η_i is the ambient noise around receiver R_{e_i} [11]. The path gain $G(T_{e_m}, R_{e_i})$ is usually a function proportional to the reciprocal of the square of distance between T_{e_m} and R_{e_i}. Thus, the farther T_{e_m} and R_{e_i}, the smaller $G(T_{e_m}, R_{e_i})$.

According to (2), the SINR at edge e_i is defined as

$$\theta(e_i) = \frac{G(T_{e_i}, R_{e_i}) p(T_{e_i})}{I_{f(e_i)}}. \qquad (3)$$

From (2)(3), one can see that when $I_{f(e_i)}$ increases, to maintain the same SINR, the power $p(T_{e_i})$ needs to increase accordingly. Nevertheless, the increase of $p(T_{e_i})$ also enlarges the interference of other links. Therefore, other links also need to boost their power to maintain the same signal quality. The minimum power of each edge to maintain the required SINR can be obtained by solving the linear equation,

$$(I - F)p = b, \qquad (4)$$

in which

$$F(i,m) = \begin{cases} \dfrac{G(T_{e_m}, R_{e_i}) c(e_i)}{G(T_{e_i}, R_{e_i})}, & m \neq i \\ 0 & m = i \end{cases}, \text{and} \qquad (5)$$

$$b(i) = \frac{c(e_i)\eta_i}{G(T_{e_i}, R_{e_i})}$$

where $c(e_i)$ is the required SINR at edge e_i.

Let p_T be the power consumption estimation made by the sensor node T_{e_i}, and F_T and b_T the matrix and vector defined in (5). Let p'_T, F'_T and b'_T be the corresponding vectors and matrix for the case that assuming edge e_i is occupied. The increased power consumption for using edge e_i is

$$\Delta p_T^{(i)} = p'_T - p_T \approx (I - F_T)^{-1}(\Delta F_T p_T + \Delta b_T) \qquad (6)$$

where $\Delta F_T = F'_T - F_T$ and $\Delta b_T = b'_T - b_T$.

Although this model is used in many related problems in wireless networks [6][12][13], several difficulties will encounter when applying it directly. First, this model needs a matrix that keeps the information of path gains between all pairs of edges, which change dynamically and therefore frequently updates are required. Second, to obtain the solution, a big linear system needs be solved. Although distributed iterative methods for solving large linear systems are available, the required computation and communication are still too expensive for WSNs. Last, the goal of the power calculation is to estimate the impact of using a link for transmission, which has exponential many combinations. It is not practical to evaluate all possible combinations and to pick a route. A distributed and practical power estimation model will be presented in Section 3.

2.3 Related work

Routing algorithms in WSN has received massive research attention. From classical shortest path to geographic greedy forwarding, most algorithms focus on routability, computational cost, and routing distance, and only few of them are designed to minimize the power consumption or interference avoidance.

For interference avoidance WSN communication methods, diverse approaches had been proposed. In [4][7], the multi-channel technique is utilized to reduce the interference between the communication of different channel. The channel assignment is static and off-line, which may waste available bandwidth and restrict the possible routing paths. In addition, the number of channels is limited, which makes those methods poor in scalability.

In [2][3][18], authors proposed link scheduling methods that avoid the concurrent communication of nearby links. They can be viewed as another type of multi-channel method (time division). However, the problem is NP-hard, and the algorithms are not distributed and hard to satisfy the dynamic requirements. Although scheduling is essential to avoid concurrent sends and receives, practically, the timing control in WSN is very difficult. In this paper, we assume some scheduling method is applied, and the requested bandwidth of transmission has already taken the scheduling time into account.

Few interference avoid routing algorithms had been proposed. In [5], the communicating nodes and its neighbor nodes are blocked such that no concurrent communication can for communicating nodes and its neighbors. However, this method can cause low utilization of sensor nodes and may result poor routability. In [6], the authors obtained an optimal routing path based on the result of SINR transform. This algorithm resolves the problems occurred in [5] and reduces the power consumption in a sensor node. However, the computation of optimal routing path is based on the shortest path algorithm, which is expensive and unsuitable in WSN.

The proposed algorithms integrate several techniques mentioned above. First, the neighborhood identification of each sensor node is similar to the blocked nodes marking process proposed in [5]. However, we use this information in power estimation. Second, we referenced the power consumption and SINR formulation used in [6] to measure the link cost. Last, our routing algorithms are based on, but not limited to, the geographic routing methods. The following subsection reviews and illustrates the four used ones in the experiments.

2.3.1 Geographic routing algorithms

Most greedy geographic routing algorithms decide a route from a source node to a destination node hop-by-hop. Each intermediate transmission node, including the source node, selects an adjacent sensor node that is proximal to the destination node. The distance is measured by the straight Euclidean distance from the transmission sensor node to the destination node. This greedy strategy works very well if the selected route does not have any traps, which are local minimums but not the destination.

Various geographic routing algorithms are designed to resolve the trapping problem. In [8], GPSR uses right hand rule to conquer local minima problem. The right hand rule delivers message to right hand neighbor when node is in a local minima. In [9], the face routing is introduced, which detects network graph feature and divides it into sub network (face). Then, face routing algorithm transmits message face by face. It can avoid local minima and holes in WSNs. In [7], the GOAFR+ algorithm is proposed, which uses geographic greedy forwarding first, and resolves the trapping problem by using face routing. In [10], the RandHT algorithm is proposed to avoid hole problem. It uses geographic greedy forwarding in general situation. When encountering a local minimum, it splits the neighbored network into four stages and chooses landmark in each stage. Then, routing algorithm set the chosen landmark as temporary destination to detour round the hole in WSNs.

3. Interference power

The theoretical power model presented in Section 2.2 faces two major computational challenges. First, it requires global information, and second, it needs to solve a linear system. Here we present a more practical SINR model and a computational method to estimate the required power of a single hop transmission. Similar idea had been proposed in literature, such as [6].

3.1 Local SINR model

The model we proposed is called the local SINR model which approximates the theoretical one derived in (4). The local SINR model of a link only considers the interference caused by the communications in its neighborhood. The reason is the path gain $G(T, R)$ decays quickly for far separated nodes, and therefore their interference can be ignored.

We define the neighborhood of an edge e_i by the neighborhood of its transmitter sensor T_{e_i}. Let $N(T_{e_i})$ be the sensor nodes in edges in T_{e_i}'s neighborhood. An edge e_m is in ei's neighborhood $N(e_i)$ if and only T_{e_m} and R_{e_m} are in $N(T_{e_i})$. The range of T_{e_i}'s neighborhood is defined operationally. If a sensor node A can receive the signal transmitted from T to sensor node B with signal strength larger than a threshold δ_N, then sensor node A is in the neighborhood of T. In another word, the set of neighborhood is larger than the adjacent sensor nodes.

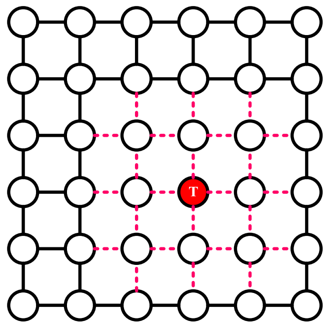

Figure 3. Solid node is current routing node. The calculation elements are dashed link for local SINR calculation model in grid.

In a grid topology, the transmission range is assumed to be the same for every transmission link. Therefore, we define the neighborhood of a sensor node as the nodes that within two-hop distance, as shown in Figure 3.

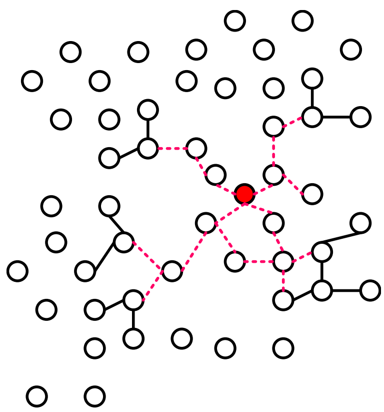

Figure 4. The calculation elements are dashed links for local SINR calculation model in random distribution.

For irregular topology, the neighborhood of a sensor node *i* is defined as a set of sensor nodes within a fixed distance from *i*. Practically, this neighborhood set can be located by sending probing signals. Initially, each sensor node *i* can send a signal to discover its neighborhood. If its nearby sensor nodes detect the probing signal with strength larger than some threshold, then they acknowledge this probing signal and join node *i*'s neighborhood. Figure 4 shows an example of the neighborhood of a sensor node in an irregular topology.

3.2 Power consumption estimation

For each edge e_i=(T_{e_i} , R_{e_i}), we estimate it power consumption by

$$\Delta p_{e_i} = \frac{\sum_{m:m\in A\left(T_{e_i}\right)} G(e_m)\times p_{e_m} + \eta_i}{G\left(T_{e_i}, R_{e_i}\right)} \quad (7)$$

where $A\left(T_{e_i}\right)$ is a set of edges e_m which are in T_{e_i}'s neighborhood and is active. An edge e_m is called active if there is a message passing from T_{e_m} to R_{e_m} at the moment that e_i is requested. The value p_{e_m} is the power consumption required for T_{e_m} sending messages to R_{e_m}. To measure p_{e_m}, the sensor node T_{e_m} runs a test route to get this information in the beginning and passes the value to its neighboring nodes.

To calculate (7), sensor node T_{e_i} sums up the $G(e_m) \times p_{e_m}$ for its active neighboring edge e_m. This information of $G(e_m) \times p_{e_m}$ for neighboring edge e_m is maintained in a table in T_{e_i}. The active information is obtained via a protocol, as stated follows. First, by the broadcasting nature and the property of the neighbor nodes, a transmission originated by a node can be received by all its neighbor nodes, and therefore neighbor nodes can use the ID (or coordinates) of sender and receiver to identify which link is used. When a transmission ends, the transmitter needs to broadcast a special signal to inform its neighbors to update the information again.

The calculation of (7) can be done quickly since all the information can be gathered by table lookup. And because the number of neighboring nodes and edges is small, the cost to store the information and the cost to calculate (7) is cheap.

4. Energy Efficient Geographic Routing Algorithms

The problems of energy effective routing, defined in (1), can be viewed as multi-objective optimization problems, which need to minimize both the routing distance and the power consumption. Since the algorithms are distributed, all the information need be obtained from local. Section 3 describes how the power consumption information can be estimated locally. For the distance and routing information, we draw the support from the geographic routing algorithms, which utilize the Euclidean distance to measure the quality of next hopping node.

The remaining problem is how to combine those two kinds of information to achieve energy efficient routing. We introduce two algorithms, which are based on some geographic routing methods, to solve this multi-objective optimization problem.

4.1 EEGRA I

The first algorithm, called EEGRA I, merges two objectives by a weighted sum. For each edge, it defines a cost function by combining the distance to destination and the interference power:

$$w_i = \mathrm{dist}(T_i, d) + \rho\Delta p_i \quad (8)$$

where dist(T_i, d) is the Euclidean distance from the transmitter node T_i to the destination node d, ρ is positive number, and Δp_i is the increased power consumption defined in (7).

The EEGRA I algorithm is a distributed algorithm which employs greedy geographic routing algorithms to find the route based on the cost function defined in (8). The problem at each sensor nodes becomes to find a next hop with minimum w_i,

$$\min_{e_m \sqsubseteq A(T)} w_{e_m} \quad (9)$$

The procedure of how each senor node responds after receiving a message is sketched in Algorithm 1.

Algorithm 1: Procedure of message handling for each sensor node of EEGRA I.

Input: A message containing the coordinate of the destination SN *d*.

Output: Next hopping node

Algorithm:

If *Current_node ≠ Destination_node*

1. Calculate link weight w_i of theg links around current node.
2. Choose the node with the smallest weight as the next hopping.
3. When it is trapped in a local minimum, resolve it by the geographic routing algorithm.
4. Transmit message to next hopping node.

End If

It can be seen that the procedure is just like most geographic routing algorithms, except the definition of cost function. Step 3 in Algorithm I varies for different used geographic routing algorithms. Details can be found in literature.

The time complexity analysis depends on the used geographic routing algorithms, as well as the graph models they employed. Although we defined our graph by visibility, which is easier to define the power model, in routing other types of graphs, such as Relative Neighborhood Graph (RNG) , Gabriel Graph (GG), or Restricted Delaunay Graph (RDG) [8][19], may be used in the underlying geographic routing algorithms. Those graph models have better properties in the analysis of time complexity. To simplify our analysis, we give some assumptions on the power consumption, computed routes, and sensor node distribution.

Assumptions:

(1) The maximum power consumption is bounded, $\Delta p_i \leq \varphi$.

(2) In a route computed by EEGRA I, no cross links.

(3) The length of edges on the path is normally distributed with mean ℓ.

Lemma 4.1: *If there is no local minimum in the route computed by EEGRA I, which means $w_1 > w_2 > \ldots > w_m$ for the cost functions along the computed route $\{s, t_1, t_2, \ldots t_{m-1}, d\}$, and assumption* (1) *is satisfied, then $dist\ (t_i, d) < dist(s,d) + \rho\varphi$ for $i=1, 2, \ldots, m-1$.*

Proof: From the monotonic decreasing property of w_i, $w_i > w_{i+1}$, one has

$$\mathrm{dist}(t_i, d) + \rho\Delta p_i > \mathrm{dist}(t_{i+1}, d) + \rho\Delta p_{i+1}.$$

If $\mathrm{dist}(t_{i+1}, d) > dist(t_i, d)$, it can be written as

$$\mathrm{dist}(t_{i+1}, d) - \mathrm{dist}(t_i, d) < \rho(\Delta p_i - \Delta p_{i+1}) \leq \rho\varphi.$$

Above relation can be extended to $\mathrm{dist}(t_{i+k}, d) - \mathrm{dist}(t_i, d)$ by induction if one only picks t_j that makes $\mathrm{dist}(t_j, d)$ increases,

$$\mathrm{dist}(t_{i+k}, d) - \mathrm{dist}(t_i, d) < \rho(\Delta p_i - \Delta p_{i+k}) \leq \rho\varphi.$$

Setting $t_i = s$ in the above inequality, one can obtain the result. ♦

Lemma 4.1 shows if there is no local minimum, the distance of the nodes in the computed route to the destination is bounded. Thus, all the intermediate sensor nodes are in the circle, centered at d, with radius $\mathrm{dist}(s,d) + \rho\varphi$. Using the similar arguments in the proofs of [19], we have the following theorem.

Theorem 4.2: *If there is no local minimum in the routing, and assumption* (1)(2) *are satisfied, then the length of the route computed by EEGRA I is of $O((dist(s,d) + \rho\varphi)^2)$.*

With theorem 4.2 and assumption (3), we can get the expected number of hops for EEGRA I.

Theorem 4.3: *If there is no local minimum in the routing, and all assumptions are satisfied, then the expected number of hops the route computed by EEGRA I is of $O((dist(s,d) + \rho\varphi)^2 / \ell)$.*

4.2 EEGRA II

The second algorithm, called EEGRA II, is to combine those two kinds of information by putting the power consumption in the constraints. Initially, we discretize the possible powers into several power-levels, and then guess a power level $p_{\max}$ as the maximum power consumption in the routing paths, $p_{\max} = \max_{e_i \in R(s,d)} \Delta p(T_{e_i})$. When the source sensor transmits a message, the information of $p_{\max}$ is also sent with the message. Each intermediate sensor node T only considers the edges whose power consumption is less than or equal to $p_{\max}$, and chooses one feasible edge with the minimum distance to the destination. The procedure of how each sensor node responses is sketched in Algorithm 2.

Algorithm 2: Procedure of message handling for each sensor node of EEGRA II.

Input: A message containing the coordinate of the destination SN d and the maximum allowed power consumption $p_{\max}$.

Output: Next hopping node

Algorithm:

If *Current_node ≠ Destination_node*

1. Choose the node with the smallest distance to destination d whose $\Delta p(e_m) \leq p_{\max}$.
2. When it is trapped in a local minimum, resolve it by the geographic routing algorithm.
3. Transmit message to next hopping node.

End If

This algorithm is similar to I2MR [5], which blocks edges that was affected by the interference or requires large power consumption. The difference is that when the routing fails, EEGRA II algorithm will try the next power level, which increases the maximum power consumption allowance, and the number of feasible communication edges. The high level description of EEGRA II is given in Algorithm 3.

Algorithm 3: the EEGRA II algorithm

Input: Source node s, destination node d, network graph $G(V,E)$, and power-levels $p_1 < p_2 < \ldots < p_k$.

Output: Energy-efficient routing path r

Algorithm:

For $p_{\max} = p_1, p_2, \ldots, p_k$

1. Block the edges whose power consumption are larger than $p_{\max}$.
2. Use the default geographic routing algorithm to find the routing with the use of feasible edges only.
3. If a route is found, stop.

End For

The routes found by the EEGRA II does not optimize the objective function (1), but the following one,

$$\arg\min_{R(s,d)\sqsubseteq E} \sum_{e_i \in R(s,d)} |e_i| \quad (10)$$
$$\text{subject to} \quad \theta(e_i) \geq \theta_0$$
$$\Delta p(T_{e_i}) \leq p_{\max}$$

This objective function is not optimal in the global sense, which means it does not minimize the total power consumption of the entire sensor network. However, it make more sense for a WSN, because it is to minimize the power consumption of each sensor node. Thus, the power consumption of each sensor node in a route can be constrained by $p_{\max}$.

The feasibility of EEGRA II can be verified easily, because if we set $p_{\max}$ equal to the maximum power Δp, which means no any restriction, EEGRA II goes back the default geographic routing algorithms it invokes. If we restrict $p_{\max}$ to some very small values and only consider the interference, not the total power consumption, then it works like the I2MR algorithm, in which many links are blocked. The problem is how efficient this method is, in terms of time complexity and power saving.

Theorem 4.4: *Let $O(T(n))$ be the time complexity of the geographic routing algorithm used in EEGRA II, and k be the number of energy levels defined in Algorithm 3. The time complexity of EEGRA II is $O(kT(n))$.*

Proof: The proof is straightforward from Algorithm 3. Since EEGRA II may try all possible energy levels, and for each energy level, it run the underlying geographic routing algorithm, the worst case time complexity is $O(kT(n))$. ♦

The performance of energy saving of EEGRA II really depends on the used geographic routing algorithm. Take the case in Figure 1 as an example. If the Face routing algorithm is used, it will choose Pass 3, which although has the smallest Δp for each hop, but the total power consumption is the highest. We will validate the effectiveness of power consumption for each accompanied geographic algorithms empirically in Section 5.2.2.

Another important factor that influences the power consumption is the number of power level. Intuitively, the more level of power constraints, the better power saving we can obtain because it releases just enough edges for data transmission. However, the real situation may be more complicated. For finer energy levels, the more number of iteration needs to run to find a feasible route. This does not increase the power on routing, but also the power in computation. In fact, according to our experiments, as reported in Section 5.3, sooner after the number of power-level exceeds a threshold, the power saving won't be improved.

5. Simulations and Results

In this section, we present the results of experiments to scrutinize the routing path selection based on the EEGRA algorithms. Furthermore, we use simulations to compare the effectiveness of EEGRA algorithms with existing ones, in terms of time complexity, power consumption, and packet received ratios.

We implemented the EEGRA algorithms based on four geographic routing algorithms: GPSR[8], GOAFR+[7], Face Routing[9] and RandHT[10], and other algorithms for comparision, including SINR-based [6], I2MR [5] and the four geographic forwarding algorithms [7][8][9][10]. All the experiments and simulations are integrated NetSim2 and our own codes are developed in C.

5.1 Computed Routing Paths

In this subsection, we compared the routing paths of three types of routing algorithms: the EEGRA algorithms, the SINR-based algorithm [6], and the pure geographic greedy algorithms [7], in the case when there are some ongoing transmissions in the neighbor.

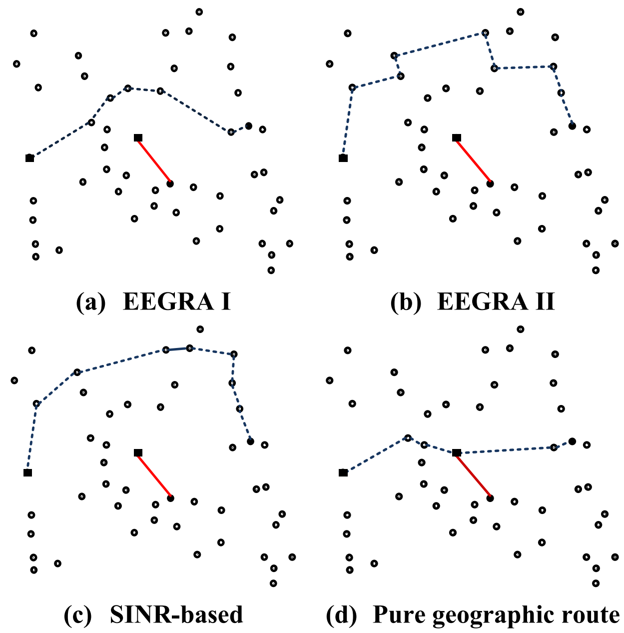

Figure 5. Experiment result of EEGRAs, SINR-based and pure geographic forwarding algorithms

Figure 5 shows the routing paths calculated by four algorithms, in which there is an ongoing transmission, marked in the red solid line. And a new transmission is requested from the source node (solid square) to the destination node (solid circle). As can be seen, both EEGRA algorithms and SINR-based algorithm detour to avoid the ongoing transmission, Figure 5(a)-5(c), while the pure geographic greedy algorithm forwards messages to the nearest neighbor nodes.

5.2 Simulations

The experiments in this section aim to verify the performance, power-efficiency and routability of EEGRA algorithms. Hence, we engage in some experiments that includes routing speed, power consumption, the integrity of received packets, the numbers of transmission tasks in network topology at same time.

The simulations consist of a random distribution network with 50 ~ 5×10^6 sensor nodes on a 1000×1000 unit plane. Moreover, we set the system parameters based on ZigBee™ IEEE802.15.4 [20] specification, such as: 2.4GHz frequency and 250Kbps transmission bandwidth and some parameters used in [1][11]. We set ambient noise to 5×10^{-8} and path loss exponent equal to 2. The numbers of routing task are ranged from 10^2 to 10^6 and every transmit task size is fixed at 100 KB, and the minima required SINR θ_0 is fixed at 0.1.

5.2.1 Routing Efficiency

In general, the EEGRA and the SINR-based algorithms enable to obtain a power-efficient path to forward messages. However, the SINR-based algorithm has time complexity O(n^3) and requires global information. In contrast, the EEGRA algorithms, inherited from pure geographic routing algorithms, are fully distributed and of time complexity is similar to the used geographic routing algorithms.

Figure 6 compares the running time of 13 algorithms for different numbers of transmission tasks. The algorithms in comparison include four geographic routing algorithms: GPSR, RandHT, Face routing and GOAFR+, four EEGRA I algorithms with four geometric routing algorithms, four EEGRA II algorithms with four geometric routing algorithms, and the SINR-based algorithm. The number of sensor nodes is 1000, and the number of transmission varies from 100 to 1000.

The results show the running times of geographic algorithms and the EEGRA algorithms are similar, and grow almost linear with the number of transmissions. On the other hand, the SINR-based algorithm is the most time consuming algorithm and it scales poorly even with the number of transmissions.

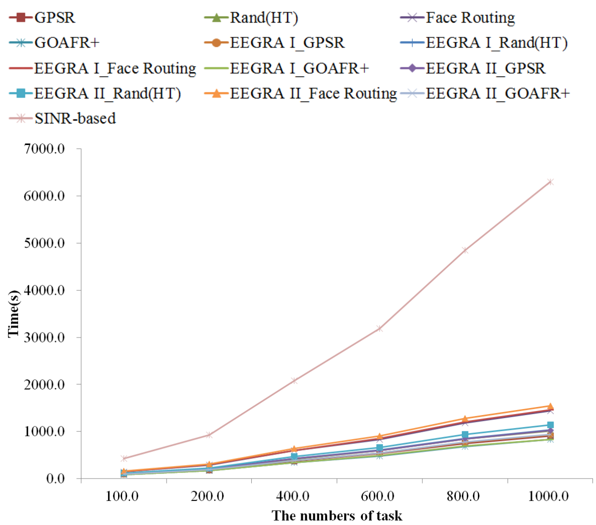

Figure 6. Simulation time for routing algorithm the number of node = 1000

In pure geographic routing algorithm, GOAFR+ is the fastest one in general. In [7] [20], GOAFR+ routing time complexity is optimal on the Gabriel Graph model in the proof. Face routing is the slower geographic routing algorithm in our experiment. Face routing time complexity is O(n) for n sensor nodes. Our experiments, with and without energy-aware, conform this theoretical result.

5.2.2 Power-efficient

This experiment verifies the power efficiency of 13 routing algorithms, same as those in Section 5.2.1, with 10^2 to 10^3 transmission tasks for 1000 sensor nodes. The results are shown in Figure 7, by which one can see that the power consumptions of the routes calculated by four pure geographic greedy routing algorithms (they are overlapped in the figure) grow more rapidly, and reach 7500mW for 1000 tasks. One the other hand, the power consumption of the route calculated by the EEGRA algorithms and the SINR-based algorithm slowly increased with the number of transmission tasks, and reach 4000mW to 4800mW for 1000 tasks.

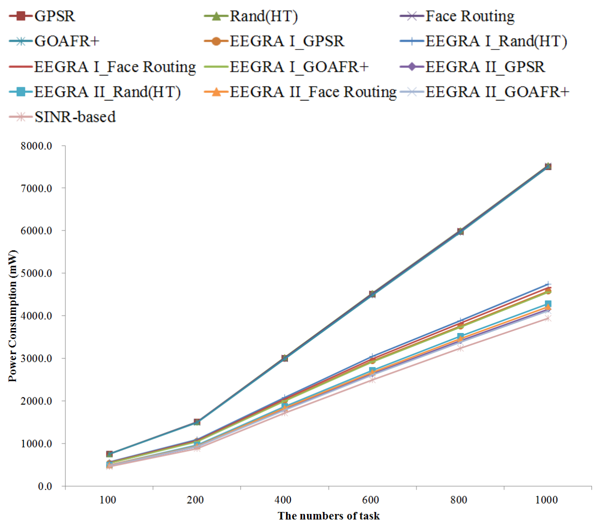

Figure 7. Power consumption (mW) for routing algorithm the number of node = 1000

In Figure 7, the SINR-based routing algorithm is of the best power efficiency. EEGRA algorithms can achieve similar power efficient routings. Among them, the EEGRA II algorithms perform better than the EEGRA I algorithm in terms of power efficiency.

Figure 8 presents how much energy saving is made by different energy efficient algorithms. The measurement is defined by the energy saving comparing to the power consumption of the geographic routing algorithms. Let P_{gra} be the power consumption of a geographic routing algorithm and P_{ee} be the power consumption of a energy efficient routing algorithm. To make comparison easier, we use relative energy saving, which is defined as

$$\text{energy saving} = 1 - \frac{P_{ee}}{P_{gra}}. \tag{11}$$

We use the power consumption of GOAFR+ as the reference base, and compute the energy saving for eight EEGRA algorithms and the SINR-based algorithm. As shown in Figure 8, the SINR-based algorithm is the best, which can save 40%-50% energy comparing to the pure geographic routings. EEGRA II algorithms, four of them, can save 35% to 45% power consumption. EEGRA I algorithms are in the bottom, which can still save 25% to 35% energy.

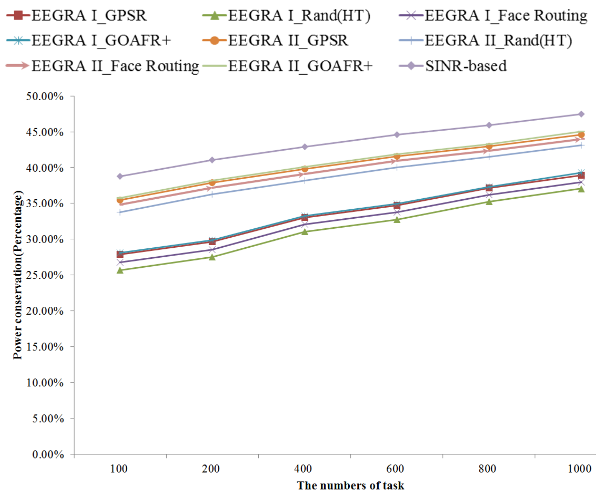

Figure 8. Power saving of the routing algorithms for the number of sensor node = 1000

In Figure 8, the most power ineffective geographic routing algorithm, cooperated with EEGRA I and EEGRA II, is the RandHT. This phenomenon can be reasoned as follows. In energy efficient comparison, there are two factors: the routing distance and the interference, as shown in the example of Figure 1. The RandHT algorithm uses some congestion control technique to avoid congestion zone, which gives better routability, but the routes it computes may be longer than others. Since our algorithms avoid interference of transmitting nodes, which also serves similar functionality as congestion control, the advantage of the RandHT is not so effective. Therefore, the algorithms that choose shorter paths could save more power consumption.

5.2.3 The reliability of the routing

The routability of routing algorithms is the ability to find routes for given sources and destinations. In this experiment, we use packet arrival ratio to measure the routability of routing algorithms, which is defined as follows,

$$\text{packet arrival ratio} = \frac{\text{number of satisfied requests}}{\text{number of routing requests}} \qquad (12)$$

There are several reasons that make the sensor nodes unavailable for data transmission. The first reason is each sensor node cannot physically process more than one data transmission at the same time. Therefore, when there are more data transmission requested simultaneously, the number of available sensor nodes will drop. The second reason is caused by interference-avoid routing algorithms, such as I2MR, which will block some sensor nodes that near the working sensor nodes to avoid the interference. EEGRA II algorithm also blocks some sensor nodes according to the desired interference levels.

Figure 9 shows the results of various routing algorithms for different number of transmission tasks. The result can be divided into three groups. The first group is the pure geographic routing algorithms. The second group includes the EEGRA algorithms and the SINR-based algorithm. The third group only has one algorithm, which is the I2MR algorithm [5]. As can be seen, the packet arrival ratio of the first group is about 85%, and is about 80% for the second group, but is only around 70% for the I2MR algorithm.

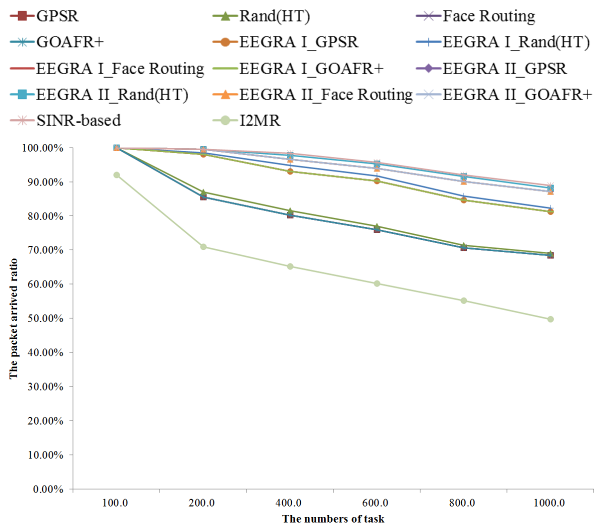

Figure 9. Packet arrival ratio of routing algorithms for the number of sensor node = 500

5.3 Power-level affection of EEGRA II

In EEGRA II, each routing task is assigned a minimal power-level $p_{\max}$, and only the links with Δp less than $p_{\max}$ is usable. In this section, we experiment different power-level settings of EEGRA II algorithm to explore its affection of energy saving.

Figure 10 shows the experimental result of power consumption and running time of EEGRA II for using different numbers of energy levels. The number of sensor nodes and the number of tasks are fixed to 1000 and 1000 for all the different energy levels. The routes for different energy-level setting may be varied. As shown in the figure, the power consumption is decreasing as the number of energy-level increases, and converges after the number of power-level exceeds 10. The running time is increasing gently with the power-level. If one adds the power consumption of computation to the entire power measurement, there will be an obvious minimum of the power consumption curve.

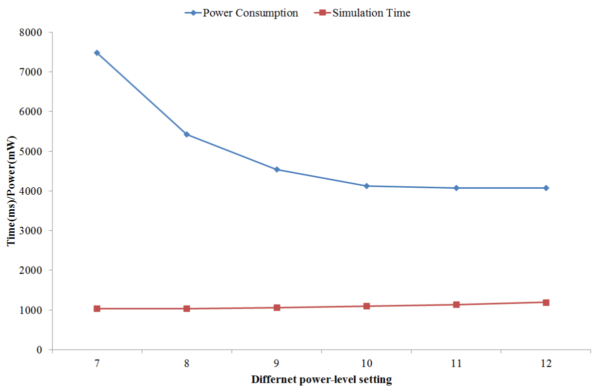

Figure 10. Power consumption and running time by using EEGRA II with different power-level settings.

6. Conclusion and Future Work

This paper proposes two energy efficient routing algorithms, called EEGRA, which consider all three factors that affect the power consumption of routing: routing distance, interferences, and computational cost. The basic routing of EEGRA is driven by geographic routing algorithms, and the power term is added to the objective function and constraints for those two algorithms respectively. Our experiments show the EEGRA algorithm uses similar time as the geographic routing algorithms, and can also achieve similar power savings as the optimal SINR-based routing algorithm. In addition, it has better routability comparing with the I2MR algorithm.

For future work, we plan to analyze the best parameter setting ρ for the EEGRA I algorithm. For the EEGRA II algorithm, we plan to develop automatic method to decide the optimal power-level setting for the given environment. In addition, we consider the adaptive method to decide the power-level of EEGRA algorithms, which may work like binary search, but based on the current network traffic. Last, we also consider integrating the more recent routing algorithms, such as virtual coordinate method or hierarchical routing methods, to develop new energy efficient routing algorithms.

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