SI-INSPIRED ENERGY AWARE QoS ROUTING TREE FOR WSN

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Abstract: A heuristic theoretical optimal routing algorithm (TORA) is presented to achieve the data-gathering structure of location-aided quality of service (QoS) in wireless sensor networks (WSNs). The construction of TORA is based on a kind of swarm intelligence (SI) mechanism, i.e., ant colony optimization. Firstly, the energy-efficient weight is designed based on flow distribution to divide WSNs into different functional regions, so the routing selection can self-adapt asymmetric power configurations with lower latency. Then, the designs of the novel heuristic factor and the pheromone updating rule can endow ant-like agents with the ability of detecting the local networks energy status and approaching the theoretical optimal tree, thus improving the adaptability and energy-efficiency in route building. Simulation results show that compared with some classic routing algorithms, TORA can further minimize the total communication energy cost and enhance the QoS performance with low-delay effect under the data-gathering condition.

Key words: wireless sensor networks(WSNs); swarm intelligence(SI); routing; energy aware; quality of service (QoS)

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INTRODUCTION

Data-gathering is a critical operation in wireless sensor networks (WSNs) for extracting the useful information from the operating environment to the base station sink. Constrained by the limited and non-replenished energy resources, minimizing energy consumption is regarded as a major performance criterion to provide the maximum network lifetime in WSNs. Technologies used to balance the energy consumption in networks are universally accepted as a key factor for prolonging the lifetime[1-2]. However, without the geographic information support, the periodic low-rate data flooding throughout the network would cost lots of energy. Therefore, many current researches[3-6] focus on energy optimizing location-aided routing protocols with both low power and fault tolerance to overcome the above disadvantages. And the core technologies in above researches are realized by efficiently using geographic-aware information to limit the new route search into a smaller "request zone", which is estimated according to the prior position and the mobility information of destination, thus conserving more energy. The size of the "request zone" is too large if the obtained information is inaccurate. To solve the above problems, the greedy perimeter stateless routing (GPSR)[7] is proposed to utilize the greedy decisions forwarding perimeter-mode packets in a derived simple planar graph. The energy of those nodes on the planar graph should be

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quickly depleted for concentrated traffic on the promiscuous listening mode. The above routing problems can be proved by NP-hard. Swarm intelligence, which is the emergent collective intelligence of groups of simple agents, is an efficient way to solve the concerned problems. Swarm is a population of interacting individuals, which contributes to optimize some global objectives via collaborative operations. As an important research domain of swarm intelligence, ant colony optimization (ACO) is a constructive meta-heuristic optimization method and has been successfully used to build energy-saving routing[8-10]. In the process of routing construction in WSNs, ant-like agents concurrently and asynchronously build optimal solutions via applying a stochastic local decision policy and using pheromone trails and heuristic information. However, those swarm intelligent themes only put emphasis on the positive-feedback mechanism to search optimization and have made some modifications to fit different network types, which cannot satisfy the special characteristics of WSNs. This paper proposes a heuristic theoretical optimal routing algorithm (TORA). In the algorithm, prior theoretical results can be combined with the swarm intelligence-inspired mode to further enhance the energy-efficiency of routing construction in WSNs.

1 SYSTEM MODEL

WSNs can be represented by a weighted undirected graph $G=(V,E,W)$, where V and E represent the set of nodes and links in G respectively, while W denotes the set of weights with $E\subset G$. Each link $<i,j>\in E$ is associated with a delay parameter $D_{<i,j>}\in W$ and the total delay requirement for QoS is set as $D_{\text{Threshold}}$. In WSNs, the energy consumption of sensors should be unbalanced for the asymmetric traffic distribution in data flow. In the data-gathering routing rooted at sink, the energy cost of each sensor is related with its own locality hierarchy in the tree structure. If the geographical position of sensor is closer to the sink, its hierarchy in the tree structure and its corresponding energy cost are higher due to the large amount of data aggregation. According to the above analyses, WSNs are divided into three categories of functional regions according to the event radius (ER) model[11] with disparity in the energy cost caused by the unbalanced streams distribution. In the ER model, events are sensed by a subset of nodes $V_s\subset V$, i.e. the data-sensing region. The data-merging region $V_c\subset V$ is defined as a disk centered at sink with radius d_{crical} denoting the critical distance of the V_c boundary from the sink. And the sensors in $V_r=V-V_s\cup V_c$ compose the data-relaying region. It is assumed that each sensor node maintains the information of a cache storing neighborhood and the self-address obtained by GPS and known by sink as a priori, and each artificial ant $a_k(k=1,2,\cdots,|V_s|)$ has a memory M^k, whose components are denoted in Table 1.

Table 1 Definition of components in M^k

Component	Definition
d_{ant}	Distinguishing ant agent from data packet
p_k	Taboo list recording the path $L^{(v)}$ built by a_k
c_{hop}	Number of accumulated hops
R_i	Remaining energy level of $n_i\in p_k$

The current feasible neighborhood of a_k is defined as $A_K=(V-L^{(v)})\cap O^{(i)}$, where $O^{(i)}$ is the set of neighbors in n_i. Via the functional region division of sensor networks and the ability of ant memory, the artificial ant can roughly estimate the energy-cost-level of each reached sensor and correspondingly adjust the weight in heuristic information of routing selection to improve the reliability of data-gathering tree.

Let $R_i=E_i^{(\text{lef})}/E_i^{(\text{ini})}$, which denotes the remaining energy level of $n_i\in V$. The routing tree problem Ξ is defined to find a series of optimal paths $t_{\text{mult}}=\{p_k^*\}|_k$ from $V_s\subset V$ to destination sink subjected to the following conditions

$$\Xi:\quad \frac{1}{c_{\text{hop}}}\sum_{n_i\in p_k} R_i \geqslant \overline{R}(p_k^*)|_k$$
$$p_k^*\in t_{\text{mult}}\subset G \tag{1}$$

$$D(p_k)=\sum_{<i,j>\in p_k} D_{<i,j>}\leqslant D_{\text{Threshold}} \tag{2}$$

Eqs. (1, 2) are constraint conditions for QoS requirement of energy optimization and temporal consistency, where $\overline{R}(p_k^*)$ denotes the average remaining energy ratio of optimal path p_k^*, Ξ a NP-hard constrained path optimization (CPO) problem and solved by Lagrange multiplier (LM) algorithm. The Lagrange function is described as

$$L(p,\lambda,D_i) = \overline{R}(p) + \lambda[D_i - D(p)] \quad D_i \in [0, D_{\text{Threshold}}] \tag{3}$$

The solutions can be obtained by calculating the partial differential of Lagrange function matrix, but it is not suitable for the resource-limited sensor nodes in WSNs. Therefore, this paper proposes TORA algorithm to solve this primary problem Ξ with a fully distributed way in ACO approach.

2 OPTIMAL ROUTING STRUCTURE

2.1 Design of heuristic factor

It is assumed that $n_v \in V_s$ sends l bit message on multi-hop way to sink, which requires $K^{(v)}-1$ relay nodes and the ith hop distance d_i, where $K^{(v)}$ shows the number of theoretic hops from n_v to sink. Based on the first-order-radio-model[12], the energy expended by relaying l bit message over distance d_i is $E_{\text{relay}}(l, d_i) = (2E_{\text{elec}} + \varepsilon_{\text{amp}} d_i^n) \times l$. Denoting that $d(n_v, \text{sink})$ is the distance between the source $n_v (v \in [1, |V_s|])$ and sink. The total cost on path from n_v to sink is $P_{\text{total}}(d_i) = \sum_{i=1}^{K^{(v)}} E_{\text{relay}}(l, d_i)$, which can be proved as a strict convex function, and its minimal value is only obtained under the condition that each hop distance is equal to $d_{\text{optim}}^{(v)} = d(n_v, \text{sink})/K^{(v)}$ according to Jensen's inequality. And then the optimal hop-counts (Eq. (4)) is calculated by imposing the derivative operation, i.e., $\partial P_{\text{total}}(d_i)/\partial K = 0$.

$$K^{(v)} = \left\lfloor d(n_v, \text{sink}) \sqrt[n]{\frac{\alpha_1}{(n-1)\alpha_2}} \right\rfloor \tag{4}$$

where α_1 and α_2 are node energy parameters. We set vector $\mathscr{J}^{(v)}$ as the coordinate sequence of theoretical points, i.e., $\mathscr{J}^{(v)} = \{n^{(v)}(t)\}, t \in [1, K^{(v)}]$. The rectangular coordinates of each theoretical point for minimal P_{total} is deduced as follows

$$\begin{cases} x_{\text{optim}}(c_{\text{hop}}^{(v)}) = x_v + c_{\text{hop}}^{(v)} \cdot d_{\text{optim}}^{(v)} \cdot \cos\left[\arctan \dfrac{y_{\text{sink}} - y_v}{x_{\text{sink}} - x_v}\right] \\ y_{\text{optim}}(c_{\text{hop}}^{(v)}) = y_v + c_{\text{hop}}^{(v)} \cdot d_{\text{optim}}^{(v)} \cdot \sin\left[\arctan \dfrac{y_{\text{sink}} - y_v}{x_{\text{sink}} - x_v}\right] \end{cases} \tag{5}$$

At $c_{\text{hop}}^{(j)}$, the distance-error between theoretical optimal sensor and actual counterpart is calculated by Eq. (6).

$$\Delta d_j(c_{\text{hop}}^{(j)}) = [x_j - x_{\text{optim}}^{(v)}(c_{\text{hop}}^{(j)})]^2 + [y_j - y_{\text{optim}}^{(v)}(c_{\text{hop}}^{(j)})]^2 \tag{6}$$

Defining that triple $\boldsymbol{S} = (B, R, H)$ is the current state obtained by the ant agent for next hop selection, i.e., during the process of routing building, the bias B, the remaining energy level R and the hop counts H are taken into account. Assuming that state vector $\boldsymbol{S}_j = (B_j, R_j, H_j) \in \boldsymbol{S}$, and each tuple of $\boldsymbol{S}_j$ is defined as follows

$$B_j = \Delta d_j(c_{\text{hop}}^{(j)}) \tag{7}$$

$$R_j = E_j^{(\text{lef})}/E_j^{(\text{ini})} \tag{8}$$

$$H_j = c_{\text{hop}}^{(j)} \tag{9}$$

where B_j provides the location-aided energy-efficiency information for the process of path building and helps ant agent to adjust the forward direction to sink based on the bias value. R_j shows the energy status of n_j and H_j the hops of ant agent to reach the source node through node n_j. With the accumulation of hop-counts, the probability of reached n_j belonging to data-merging region V_c increases and the higher energy consumption is consequently expended. Therefore, according to the distribution trait of energy cost in routing tree, the relationship between each tuple in $\boldsymbol{S}$ is defined as Eq. (10), which indicates that the closer the current sensor to sink, the larger the weight of remaining-energy-level regarded as energy efficiency factor.

$$\tilde{\omega}_j = (H_j R_j)/B_j \quad n_j \in A_K \tag{10}$$

The cost $\tilde{\omega}_j \in W$ is associated with each $n_j \in A_K$ as local evaluation information for node robustness. The higher the value of $\tilde{\omega}_j$, the greater the probability that n_j is selected as the next hop node on the building of optimal routing path. If

$k=\mathrm{argmax}_{n_j \in A_K}\{\tilde{\omega}_j\}$, the ant at current sensor n_i tends to choose n_k as the next hop sensor. Therefore, the structure of heuristic factor for ACO is designed as

$$\eta_{ij} = \tilde{\omega}_j \quad n_j \in A_K \tag{11}$$

Eq. (11) embodies the idea that artificial ant can adaptively choose the high-energy-efficient sensor as its next hop in each step and adjust corresponding variable weight to improve the reliability of data-gathering tree. In two extreme cases, i. e., if $H_j=0$ or $E_j^{(\mathrm{lef})}=0$, then $\eta_{ij}\to 0$, which indicates that n_j belongs to data-sensing region ($n_j \in V_s$), or it runs out of energy, then the ant agent should abandon the selection of n_j during the path building.

2.2 Algorithm flow

At the initial stage of TORA, the optimal routing tree t_{mult} is empty and each sensor in $V_s \subset V$ takes sink as common destination. The sink instructs sensors in V_s to create ant-like agents for constructing optimal routing paths and compute the corresponding theoretic point sequence $\mathscr{J}^{(v)}$. The above task is sent by "interest", which also contains the address coordinate of sink, i. e., $(x_{\mathrm{sink}}, y_{\mathrm{sink}})$, and propagates through the network to V_s. The ant dispatched from sensor $n_v \in V_s$ is denoted as a_k^{forw}. In each step, a_k^{forw} chooses the next unvisited node in current feasible neighborhood with the improved transition probability given by Eq. (12) and constructs $p^{(v)} \in t_{\mathrm{mult}}$ from source to sink, if it does not meet any sensor which has been added to t_{mult}.

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{m\in A_K}[\tau_{im}(t)]^{\alpha}[\eta_{im}]^{\beta}} \tag{12}$$

When a_k^{forw} arrives at sink, the corresponding backward ant a_k^{back} is created and backes along the built $p^{(v)}$ to n_v, and any sensor visited by a_k^{back} is set with a mark, which denotes that the sensor belongs to t_{mult}. Meanwhile, a_k^{back} carries the path information copied from a_k^{forw} and deposits the pheromone trails on visited sensors according to

$$\tau_i^k \leftarrow (1-\rho)\tau_i^k + \rho \cdot \Delta\tau_i^k \tag{13}$$

where $\rho \in (0,1)$ represents the volatility degree of pheromone. Total remaining energy ratio $\sum_{n_i \in p_i} R_i$ and c_{hop} carried by a_k^{forw} are used to update pheromone.

$$\Delta\tau_i^k = \begin{cases} \Delta\tau_i^{k-1} + \lambda[\overline{R}(p_k) - \overline{R}(p_{k-1})] \\ \qquad\qquad D(k) \leqslant D_{\mathrm{Threshold}} \\ 0 \qquad\qquad D(k) > D_{\mathrm{Threshold}} \end{cases} \tag{14}$$

According to the updating rule, pheromones of those sensors in t_{mult} should be adaptively reinforced and subjected to constraint conditions Eqs. (1,2) of Ξ. a_k^{back} dies when it arrives at $n_v \in V_s$, and the optimal routing from n_v to sink is set up. In the other case, if a_k^{forw} meets $n_j \in t_{\mathrm{mult}}$, it stops further search to set the current graft sensor n_j as destination and comes back to source for re-executing the above algorithm. The algorithm is terminated when all source sensors in V_s are added into t_{mult}, which is composed of those corresponding optimal routing paths from each source sensor to sink. In TORA, it is proved that the final routing tree structure is loop-free by using the taboo list in memory of ant and the time-complexity of TORA has the linear relationship with the steps moved by artificial ants. According to the function connection between the solution quality and the steps, the optimal solution can be obtained by the concurrent processing of m ant agents in $k\log_2 m$ steps and the time-complexity is deduced as $O(mk\log_2 m)$.

3 SIMULATION RESULTS

TORA is simulated by using NS2 platform in a network of adjustable-density sensors (25—140) randomly distributed over a square of 500×500 units with the base station at (15, 480). The link layer is implemented using IEEE802.11 MAC protocol. Each sensor has tunable communication radius ξ_c ($\xi_c \geqslant d_{\mathrm{optim}}^{(v)}$). In the radio model, each radio dissipates $E_{\mathrm{elec}}=50$ nJ/bit to run the transmitter or the receiver circuitry and $\varepsilon_{\mathrm{amp}} = 100$ pJ/bit/m^2 for the transmitter amplifies. The parameters of ACO are set in Table 2.

Table 2 Experimental parameters and results

Iterations	Pheromone weight α	Heuristic weight β	Evaporating rate ρ	Constant quantity Q	Average cost $\bar{e}$	Average solution $\overline{L}$	Optimal solution L_{optim}
Stage 1 (cycle times 700)	2	8	0.6	70	0.042 9	162.04	162.72
	3	7	0.7	50	0.034 4	168.61	168.41
	4	6	0.75	40	0.043 7	165.11	165.34
Stage 2 (cycle times 800)	7	2	0.2	150	0.045 8	166.32	164.51
	8	3	0.25	200	0.047 4	160.45	161.20
	9	4	0.3	400	0.048 5	162.78	167.30

The parameter σ_{MSE} is defined as the factor to evaluate the degree of approximation between t_{mult} and the theoretical optimum counterpart.

$$\sigma_{\text{MSE}} = \sum_{n_v \in V_s} \sum_{t \in [1, K^{(v)}]} |d_t^{(v)} - d_{\text{optim}}^{(v)}| / (d_{\text{optim}}^{(v)} \cdot K^{(v)} \cdot |V_s|) \tag{15}$$

where $d_t^{(v)}$ is actual tth-hop distance and $|V_s|$ the number of sensors in V_s. The better the degree of the approximation between actual routing and the theoretical model, the less the total energy cost. The percentages of deviation among classical geographic-aided routing GPRS, minimum energy consumption routing, MEC[13], greedy algorithm[14] and TORA are compared with respect to σ_{MSE}. As shown in Fig. 1, the deviation in TORA always keeps the smallest value compared with the other schemes with an increase of node density, which denotes that TORA performs better than other schemes on the realization of minimal total energy-cost level in networks, because the prior theoretical results are adapted to the design of heuristic factor in TORA.

Energy balance analysis is shown in Fig. 2 at the node level after 80 times of transmission-operations, where R is the ratio of remaining and initial energy levels. In annular domain with center at sink and radius $r \in [5, 10]$, we randomly select 40 deployed sensors for energy-status observation by using different routing algorithms. The peak values of each curve in Fig. 2 are corresponding to the normalized remaining energy level. Simulation results show that the average level of TORA is higher than the other two algorithms (GPRS and MEC) because that the adaptive ant-agents mode is used in TORA.

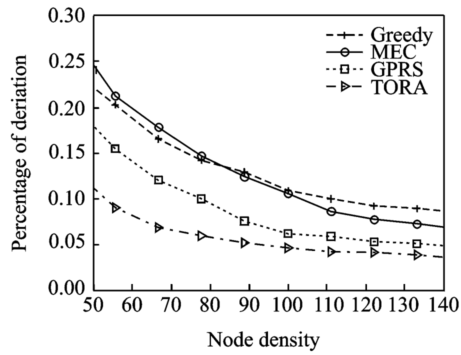

Fig. 1 Fitting degree to theoretical optimal structure

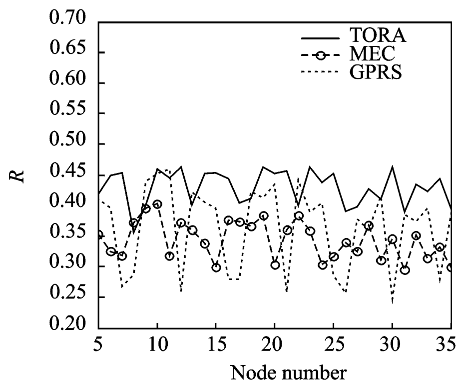

Fig. 2 Comparison of remaining energy level

In Fig. 3, based on the final routing structure t_{mult}, the performance of TORA with and without variable weight $\psi_j = R_j / B_j$ (i. e., energy factor) in heuristic factors is compared according to the number of rounds versus the survival rate of sensors. An important objective of TORA is to extend the QoS-service lifetime of WSNs, which is measured with respect to the spent time until 30% nodes in G deplete their energy. R_2 and R_1 are defined as the corresponding lower bounds of QoS-service lifetime when η_{ij} with or without the variable weight ψ_j. Fig. 3 shows that $R_1 < R_2$, which means that the QoS-service lifetime of WSNs is prolonged and the robustness of the final optimal routing tree is improved by introducing the variable weight ψ_j into heuristic factor. Therefore, TORA with variable weight outperforms that without variable weight.

Because the average delay is restricted below scheduled delay QoS-constraint, it is set as 8 ms in the simulation. Fig. 4 shows the mean of end-to-end delay comparison and the average delay of TORA is less than those of MEC and GPRS, which is benefited by the updating pheromone rule (Eq. (14)) based on the delay constraint to reinforce the trails on optimal paths and weaken the trails on those bad ones.

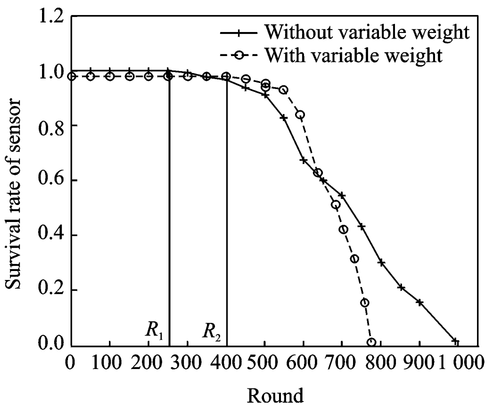

Fig. 3 Survival rate vs rounds

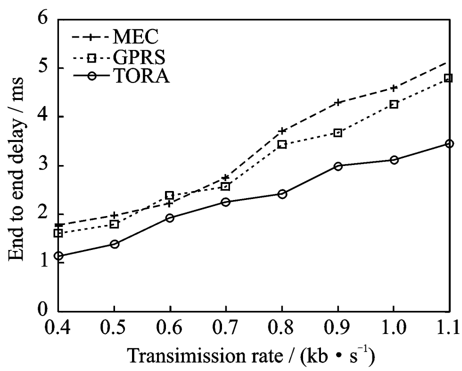

Fig. 4 End-to-end packet delay

4 CONCLUSION

For constructing the optimal routing structure in WSNs, it is important to minimize the total energy cost of data transfer from the data-sensing region to a fixed sink with delay constraint of QoS, and to improve energy robustness of routing tree structure for reducing the probability of disconnected subnets, which is caused by unreasonable energy distribution on sensors in data-gathering routing structure. This paper presents an optimal tree algorithm based on ACO, i. e. , TORA, to achieve the above two important objectives. By dividing WSNs into different kinds of functional regions, energy consumption of each sensor can be roughly estimated in advance. The novel designs of heuristic factor construction and pheromone updating rule can endow artificial ants the ability to adaptively detect the local energy status in WSNs and intelligently approach the prior theoretic model in the process of routing construction. Experimental results prove that the proposed optimal routing tree can improve the energy efficiency and the QoS-service performance of data gathering routing scheme in WSNs.

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群智能机制启发的传感器网络能量感知服务质量路由树

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摘要：提出一种理论优化路由树的启发式算法，实现地理信息辅助的传感器网络服务质量数据收集架构。算法采用群智能蚁群优化机理进行设计：首先通过构造基于流量的能量有效性权将网络划分为不同的功能区域，使得路由的选择过程能够低延时地自适应网内不均衡性的能耗状况；然后，设计了新颖的启发式因子和信息素更新规则，赋予人工蚂蚁代理感知网络局域能量状况和逼近理论优化树的能力，从而提高路由构建的自适应性和能量有效性。仿真实验结果表明，本文提出的路由机制能够在数据收集的应用背景下，有效提高收集质量和降低传输时延，并在健壮性和节能效果方面优于许多经典的传感器网络路由算法。

关键词：无线传感器网络；群智能；路由；能量感知；服务质量

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