Efficient and Density-Aware Routing for Wireless Sensor Networks

Ting Wang
Computer Science Department
University of British Columbia
guasars@cs.ubc.ca

Shuang Hao
Computer Science Department
University of British Columbia
haos05@cs.ubc.ca

Ping Wang
Computer Science College
Zhejiang University
pingwang_zju@163.com

Gang Peng
Computer Science Department
University of British Columbia
shuaige@cs.ubc.ca

***Abstract*— Point-to-point routing is central to communication networks. In this paper, we present a novel addressing and routing scheme for wireless sensor networks. We base our approach on the observation that in real applications, sensors are usually deployed in groups; while it is impractical to predict the landing location for each individual sensor, the locations of sensors from the same group tend to follow certain probabilistic model. By taking advantage of this deployment knowledge, we design a Monte Carlo sampling algorithm that distributedly discovers group-level topology of the sensor field, and represents it as a compact atlas. Meanwhile we assign each node an address comprised of its group ID and local coordinates within the group. Efficient point-to-point routing is achieved as two sub-procedures, proactive path planning on the high-level atlas and reactive actual routing using local coordinates information. In addition, our approach takes account of node density information, and prolongs the network lifetime by conserving the energy of sensors in sparse areas, which is especially important for non-evenly dense sensor networks. Experimental results show that our approach enables efficient and density-aware routing even in environment with complex topology structures.**

I. Introduction

Early sensor networks were modeled mainly as data acquisition systems, where the collected information was aggregated and routed to powerful base stations. However with increasing computing and communication capability of sensor node, the sensor networks nowadays are more like peer-to-peer systems, where individual node can perform complex data processing and storage. This trend necessitates efficient and robust point-to-point routing techniques to support a wide scope of applications, including data centric storage/retrieval [6], [16], integration with database [8], [13], etc.

Unlike networks with powerful nodes and stable connectivity, e.g., Internet, ad hoc sensor networks feature unstable communication, energy-constrained nodes and frequent topology changes. Hence it is reasonable to adopt reactive routing protocols that find a route on-demand: given the address of destination node, starting from any node, one selects a successor from the neighbors of current node. By repeatedly jumping from current node to successor, the destination is finally reached.

Assuming that the geographical locations of sensor nodes are known, a number of location-based routing approaches have been proposed [9], [10], [12]. In these schemes, the address of a sensor node can simply be its geographical location. At each step, the packet is forwarded to the neighbor closest to the destination. Geographical routing approaches are efficient in the sense that the found path is close to the optimal minimum-hop path, and the forwarding decision is made locally requiring only the location information of neighbors and destination. The main problem however lies in the requirement of exact location information, which is difficult or expensive to obtain: The equipment of each sensor node with GPS is impractical in large-scale applications; though various localization methods are proposed [2], [4], [15], they are expensive in terms of computation and communication, and moreover prone to error.

In response, a set of location-free routing schemes are proposed recently [3], [4], [5], [7], [17]. The basic idea is to assign each sensor node virtual coordinates based on its connectivity distance (minimum hop counts) to a set of beacons/landmarks. Within the virtual coordinate system, geographical routing techniques can then be applied. These methods however have their drawbacks: The virtual coordinate system may not reflect the actual geometric features, such as holes and obstacles, thus routing tends to fail in the presence of these features; the deployment of beacons/landmarks has significant influence on the effectiveness of routing, which however can hardly be studied a priori without knowledge regarding the layout of sensor nodes.

To our best knowledge, most previous routing approaches are proximity-based, i.e., packets are routed in a greedy minimum-hop manner in order to conserve energy. In simulation environment of uniformly dense deployment, the communication load is evenly distributed. In many real applications however, the sensors are deployed in groups, resulting in highly varying node density in the sensor field. In such scenarios, one is interested in conserving the energy of nodes in sparse areas, in order to guarantee the coverage of the whole network. The proximity-based approaches perform poorly for this purpose, since they make no distinction between redundant nodes and indispensable ones. This situation is illustrated in Fig. 1, where two groups of sensors are deployed. Given the source and destination nodes, the greedy proximity-based routing strategy finds a minimum hop path, which however crosses straight the sparse areas. By taking account of the node density information, one can find a better path, which is trivially longer than the greedy one, but employs much less

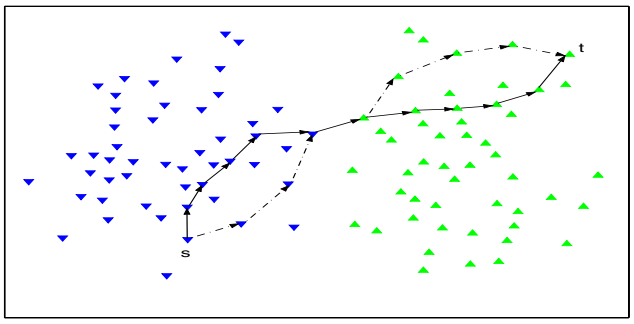


Fig. 1. Trade-off between routing efficiency and network lifetime in a non-evenly dense sensor network. The dashed line represents the path found by a greedy proximity-based routing approach; The solid line a path found by a density-aware routing strategy.

nodes in the sparse areas.

In this paper, we present a novel addressing and routing scheme for such *non-evenly dense sensor networks* aiming at overcoming the problems listed above. Specifically, we intend our approach to have the following properties:

- It is merely based on connectivity, and assumes no information regarding geographical locations of sensors;
- It requires no deployment of beacons/landmarks to provide topological guidance;
- It enables efficient and delivery-guaranteed routing even in environment with complex topology structures;
- It combines proximity and density information in routing, and achieves optimal trade-off between routing efficiency and energy conservation for sensors in sparse areas.

The remainder of the paper will be organized as follows: Section II gives an overview of our group-based routing scheme; Section III and IV describes in detail our addressing and routing approaches respectively; We present the experimental analysis in Section V; This paper is concluded in Section VI.

II. OVERVIEW

A. PRELIMINARIES

A sensor network is modeled as a communication graph $G = (V, E)$ over a set of sensors V. The edge set E describes the connectivity of V: two nodes share an edge if they can directly communicate with each other.

In real scenarios, sensors are usually deployed in groups, e.g., via airborne vehicle [4]. The sensors in a group are deployed from the same deployment point. While it is impractical to predict the landing location for each individual sensor, the locations of sensors from the same group tend to follow certain probability model. The actual distribution is application dependent. In this paper, we assume that it follows a two-dimensional Gaussian model [1]:

$$f(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{1}{2\sigma^2}[(x-\mu_x)^2+(y-\mu_y)^2]} \quad (1)$$

where (μ_x, μ_y) is the mean (center) of the distribution, and σ is the deviation.

We assume that all groups have the following properties: Each node belongs to a group, which is called its *home group*; nodes in the same group form a connected graph; the groups are of roughly same size; on deployment, each group has a unique group identifier (temporary group ID), which is known to all its members. Note that this identifier is temporary, and sensor node can change its group ID after deployment.

B. GROUP-BASED ADDRESSING AND ROUTING

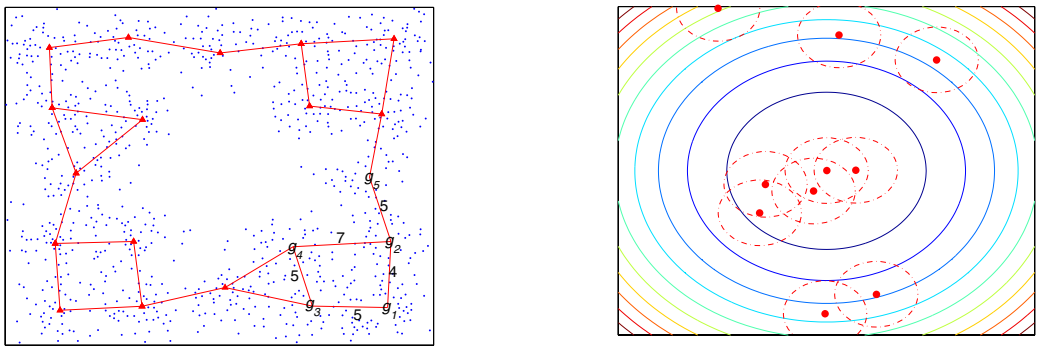
Based on the deployment knowledge, we propose a group-based addressing and routing scheme for non-evenly dense networks. The basic observations are as follows: while individual nodes may join or leave the network frequently, resulting in highly unstable connectivity, the group-level topology is much more static [5]. Thus it is possible to pro-actively pre-compute a group-level atlas to facilitate routing; every single group has simple topology structure, thus it is feasible to apply proximity-based approach to actual routing within a group using local coordinate information.

Based on these observations, our scheme realizes point-to-point routing in the following way: In the pre-processing phase, the connectivity of groups is discovered and encoded in a highly compact atlas accessible to all the sensor nodes. With the help of this atlas, the actual routing is implemented as a sequence of local reactive forwarding, which is trivial if the local coordinate information is available.

To implement this scheme, we propose the concept of *group adjacent graph* (GAG) to represent the high-level topology. Formally, for a communication graph $G = (V, E)$ of a sensor network, its GAG is a graph $G_g = (V_g, E_g)$, where V_g represents the set of groups, and the edge set E_g describes the connectivity of V_g. Two groups g_1 and g_2 share an edge $\overline{g_1 g_2}$, if there exists at least two sensor nodes $n_1 \in g_1$, $n_2 \in g_2$, and an edge $\overline{n_1 n_2} \in E$. Note that the edges of G_g are weighted by the connectivity graph distance (in what follows we will use "distance" and "connectivity distance" exchangeably, if not stated otherwise.) between the centers of the corresponding two groups. Compared with G, G_g provides a more stable, and high-level description of the underlying topology features, such as connectivity, holes and obstacles. An example of GAG is shown in Fig. 2(a) where 20 groups of sensors are deployed in a field with a hole in the middle.

While GAG provides sufficient information for global planning of routing path, one still needs an effective addressing/naming scheme that encodes local coordinates information. In our framework each sensor node is assigned a two-layer address, which consists of its group ID and local coordinates, derived from its distance to the centers of its own and neighboring groups. The group ID enables to pinpoint the node's home group on the GAG, and the local coordinates make it possible to reach the node within its group by proximity-based approaches. Note that our approach can be extended to hierarchical addressing scheme [14] to support huge scale network, by organizing adjacent groups into super-groups, and addressing sensor nodes by {super-group ID:group ID:local coordinates}.

With these constructs, distributed routing can be accomplished as two operations, global path planning and local



(a) (b)

Fig. 2. (a) Example of group adjacent graph (GAG). In a field with a hole in the center, 20 groups, each of 80 sensors are deployed. The group centers form a weighted adjacent graph based on the connectivity of groups. (b) Demonstration of Monte Carlo center election algorithm. A set of sample nodes (dark dashed nodes) are randomly selected. The one with the largest number of samples within its neighborhood (dashed circle) is elected as the center.

actual routing. Each sensor node can pre-compute a group-level routing table based on GAG, which tells the next group (one of its neighbor groups) on the optimal paths to other groups. When given a routing request, a node first looks up the table to find the next group on the path to the destination, and then chooses a successor from its neighbor nodes towards the center of the next group or the destination node, depending on whether the final group is reached.

This separation of proactive high-level path planning and reactive local routing is not new in the sensor network research. Fang et al [5] proposed a landmark-based naming and routing approach, which also realized point-to-point routing as two steps, path planning and local routing. Our work differs significantly from theirs in that we do not employ any beacon/landmark to provide high-level topological guidance. Moreover, we take into consideration the node density in routing, which is of special importance for non-evenly dense sensor networks.

III. GROUP-BASED ADDRESSING

A. GLOBAL TOPOLOGY DISCOVERY

Following we present in detail our approach of discovering global topology, which constructs GAG distributedly with light communication overheads. We also theoretically prove the accuracy of this approach.

1) Monte Carlo Center Election: In ad hoc environment, the key of constructing GAG is to identify the nodes located at the centers of the groups, which can then communicate with each other to determine the relative distances between adjacent groups. Based on the deployment knowledge, we propose a *Monte Carlo sampling* algorithm, which can find centers with high accuracy and low communication cost.

In order to lessen communication overhead, only a randomly selected subset of nodes from the group participate in the center election. As can be noticed in the two-dimensional Gaussian model, the node density grows exponentially as the distance to the center decreases, hence the sample nodes fall in the area nearer to the center with higher probability. For each sample node p, by measuring the number of samples falling in its neighborhood (e.g., within radius 5 hops) and their distance to p, we can estimate the node density at p. The sample node with highest density will be elected as the center.

The basic protocol runs as follows: Each node activates itself with certain probability, i.e., sampling rate. For example, a sampling rate of 5% means that 5% nodes of each group involve in the center election. Assume that a sample node p, receives k messages from other samples within its neighborhood, with relative distance h_i $(1 \leq i \leq k)$ respectively, its density estimation $d(p)$ is: $d(p) = \sum_{i=1}^{k} e^{-h_i^2}$. This form of estimation heuristically follows a Gaussian model.

The sample nodes then broadcast their density estimation within the group. The node with highest node density, i.e., the one receiving no higher density information from other sample nodes, automatically becomes the center. This procedure is illustrated in Fig. 2(b). Center nodes then broadcast their group IDs within adjacent groups, and estimate the relative distance to neighboring centers. By exchanging information between adjacent groups, these "mosaics" can be further composed into a global atlas. Meanwhile every node records its distance to the centers of its home and neighbor groups.

2) Proof of Accuracy: Following we prove that this Monte Carlo sampling algorithm can identify the center or near-center node with high probability (detailed proofs are referred to [18]). For the ease of demonstration, we assume $(\mu_x, \mu_y) = (0, 0)$, and rewrite the two-dimensional Gaussian distribution in polar coordinate system:

$$f(r, \theta) = \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} \tag{2}$$

Note that the accuracy is a relative measurement, depending on the parameter σ. It is trivial to prove that $\int_0^{2\pi} \int_0^{3\sigma} f(r, \theta) \mathrm{d}r\mathrm{d}\theta > 0.988$, which means more than 98.8% nodes concentrate in the circle of $r \leq 3\sigma$. Thus we evaluate the accuracy of our approach relative to 3σ.

Lemma 1: Given a radius $3\epsilon\sigma$, the expected number of samples needed to guarantee that at least one node appears in the circle $r = 3\epsilon\sigma$ is $\lceil 1/(1 - e^{-9\epsilon^2/2}) \rceil$.

This gives a lower bound of the number of samples needed to guarantee that a sample falls near the center. In real scenarios, this number is usually trivial, compared with the

total number of sensors. For example, given $\epsilon = 0.1$, we have $N \geq 23$. The actual number of samples needed depends on the accuracy requirement of the application.

Lemma 2: Given a neighborhood radius z, and the number N of sample nodes, for a node with distance l to the center, the expected number $F(l, z)$ of sample nodes within its neighborhood decreases super-linearly as l increases.

Since the expected number of sample nodes appearing in the neighborhood of a node is $NF(l, z)$, one can conclude that with high probability, the nodes close to center have more sample nodes within their neighborhood than those far from center.

B. LOCAL COORDINATES ASSIGNMENT

While the global adjacent graph (GAG) provides high-level topological guidance, within each group local coordinate information is needed in order to construct the routing path distributedly and reactively. In our framework, the local coordinates of a sensor node are defined as a distance vector, with entries as its distance to the centers of its home and neighbor groups.

Formally, a node p with $g_1, g_2, \ldots, g_k$ as its own and neighbor groups respectively, has the distance vector $V(p) = [p_1, p_2, \ldots, p_k]$ denoting its distance to the centers of these groups. This basic representation in able to support various proximity metrics, such as l_1-norm, l_2-norm and centered virtual distance [5].

The name/address of a sensor node comprises of its group ID and local coordinates. After estimating its distance to the centers of adjacent groups, each sensor node re-assigns its group ID as the identifier of the group to which it has the minimum distance. The address of node p is of the form $\{\text{group ID} : V(p)\}$. Because the addresses are defined on minimum hop counts, it is possible that more than one nodes may share the same name/address, though the case is rare in practice since most sensor nodes have multiple neighbor groups for reference. Also note that with multiple references, the nodes sharing the same address are highly likely to be close to each other, in which case one can solve the ambiguity trivially by a small-scale flooding.

In addition, for each sensor node one also estimates the node density at its location. A naive way is to count the number of nodes within its transmission range, which however is dependent on the coverage of each node. Instead we define the node density based on the deployment model. For a sensor p with distance vector $V(p) = [p_1, p_2, \ldots, p_k]$, its node density is defined as $D(p) = \sum_{i=1}^{k} e^{-p_i^2}$, which intuitively represents the influence of the densities of home and neighbor groups at that location.

IV. GROUP-BASED ROUTING

Within our framework, distributed routing is implemented as two operations, proactive path planning and reactive local routing. In the following discussion, let s and t denote the source and destination nodes respectively. Without loss of generality, we assume that s and t belong to different groups.

A. PROACTIVE PATH PLANNING

Based on the group adjacent graph (GAG) constructed in the pre-processing phase, each sensor node can pre-compute a group-level routing table, which tells the next group (one of its neighbor groups) on the optimal path to other groups. For example, in Fig. 2(a) the routing table of group g_1 is listed in Fig. 3.

Destination	g_1	g_2	g_3	g_4	g_5	$\ldots$
Gateway	g_1	g_2	g_3	g_3	g_2	$\ldots$

Fig. 3. An example of group-level routing table

The global path planning amounts to finding the shortest path on the GAG, which is trivial with the help of this routing table: by a look-up operation in the table, the sensor nodes can construct a group-level shortest path to the group containing the destination node.

B. REACTIVE LOCAL ROUTING

Assume the shortest path from s to t consists of a sequence of groups, $g_1, \ldots, g_k$, where g_1 and g_k are s' and t's home groups respectively, then the actual distributed routing consists of a series of *inter-group routing* from g_i to g_{i+1} $(1 \leq i \leq k-1)$, and one *intra-group routing* in g_k to reach t.

1) Inter-Group Routing: In the inter-group routing from g_i to g_{i+1}, one follows a path consisting of nodes with decreasing distance to the center of g_{i+1}, until hitting the border of g_i and g_{i+1}. One then enters the phase of routing from g_{i+1} to g_{i+2}.

Formally, assume that the jth entry V_j of the distance vector V corresponds to g_{i+1}, the routing follows a sequence of nodes with decreasing V_j values. Note that since the distance vectors are defined on hop counts, it is highly possible that more than one nodes share the same V_j value. In selecting the successor to which the packet should be forwarded, one also takes account of the node density information. Specifically, among the neighbors with V_j less than that of current node, one selects the candidate with the highest node density. This additional criteria embeds our preference for the path passing dense areas, in order to conserve the energy of nodes in sparse areas.

2) Intra-Group Routing: After the home group of destination node t is reached, one applies intra-group routing to relaying the packet to t. The general idea is to forward the packet to a neighbor closer to the destination t than current node. Given two nodes p and q with distance vectors $V(p) = [p_1, p_2, \ldots, p_k]$ and $V(q) = [q_1, q_2, \ldots, q_k]$ respectively, a number of distance metrics $\delta(p, q)$ can be used to measure the closeness, including l_1-norm, $\delta(p, q) = \sum_{i=1}^{k} |q_i - p_i|$, l_2-norm, $\delta(p, q) = \sum_{i=1}^{k} |q_i^2 - p_i^2|_2$, centered virtual distance $\delta(p, q) = \sum_{i=1}^{k} |(q_i^2 - \frac{1}{k}\sum_{j=1}^{k} q_j^2) - (p_i^2 - \frac{1}{k}\sum_{j=1}^{k} p_j^2)|_2$ [5] etc. We will not discuss the selection of distance metric, which is not the focus of our work. In selecting the successor, a greedy proximity-based criteria is to choose the neighbor p with the minimum $\delta(p, t)$ value in order to minimize the hop count, which however may result in a path crossing sparse area. Thus again it is desirable to sacrifice some efficiency for

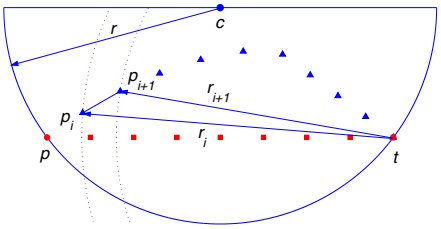


Fig. 4. Trade-off between path length and path density in intra-group routing. The square nodes present the path found by a pure proximity-based strategy, and the triangular nodes the path travelled by a density-aware routing strategy.

lessening the communication overheads on those indispensable nodes.

Compared with inter-group routing, where one proceeds towards the next group with constant speed (one hop per step), intra-group routing involves more tricky trade-off. The convergence speed may not be constant, hence one has to specify the expected progress δ_0 every step should achieve. Specifically, let p_i be the current node, $\delta(p_i, t) - \delta(p_{i+1}, t)$ indicates the progress made by selecting the neighbor p_{i+1}. Let δ_{max} denote the possible maximum progress, and the expected progress is defined relative to δ_{max}, i.e., $\delta_0 = \alpha\delta_{max}$, $\alpha \in (0, 1]$. One obeys the following rules in selecting the successor p_{i+1}: (1) p_{i+1} is closer enough to the destination t than p_i, i.e., $\delta(p_i, t) - \delta(p_{i+1}, t) \geq \delta_0$, If no such neighbor exists, one chooses the neighbor p_{i+1} with minimum $\delta(p_{i+1}, t)$ value; (2) Among all the neighbors satisfying criteria (1), the node p_{i+1} with the highest node density $D(p_{i+1})$ is selected.

Note that regardless of the distance metrics used, there can exist local minimum that may trap the routing process. In this case, a small scope of flooding (e.g., the package is broadcasted within 5 hops until a successor is found) is sufficient to find node closer to the destination than the current local minimum.

C. SETTING OF PARAMETER α

As discussed above, the parameter α adjusts the expected progress each step should achieve. In intra-group routing, it controls the trade-off between routing efficiency and energy conservation in sparse areas. Though specific αs should be set empirically for different groups, we can gain some theoretical insight about its influence on our routing approach.

To simply the analysis, we assume that the possible maximum progress δ_{max} is constant for every step. Starting from a node p, the pure proximity-based approach will follow a straight line towards t, with step-length of δ_{max}. Now instead of making the maximum progress each step, one expects to achieve δ_0 ($\delta_0 = \alpha\delta_{max}$) only, and among the candidates, the one with the highest node density is chosen. This strategy is illustrated in Fig. 4. Let c, t, p_i and p_{i+1} be the coordinates of the center of the group, the destination, the current node and the successor respectively, and r_i, r_{i+1} denote the distance of p_i, p_{i+1} to t respectively, i.e., $r_i = \delta(p_i, t)$, $r_{i+1} = \delta(p_{i+1}, t)$. The selection of successor p_{i+1} is equivalent to the following optimization problem:

$$\begin{aligned} &\text{minimize} \quad \delta(p_{i+1}, c) \\ &\text{s.t.} \quad r_i - r_{i+1} \geq \delta_0, \quad \delta(p_{i+1}, p_i) \leq \delta_{max} \end{aligned}$$

We evaluate the impact of α on the performance of our approach using two metrics, *path length* and *path density*. The former is the hop count of the path, indicating routing efficiency, while the latter is the average node density of nodes on the path, indicating how well the routing approach bypasses sparse areas. An numerical simulation (details are referred to [18]) shows that α in the range of $(0.3, 0.4)$ provides a good trade-off between path length and path density.

V. EXPERIMENTAL ANALYSIS

In this section, we present the experimental analysis of our addressing and routing scheme with two aims:

- To evaluate the correctness of our approach. Specifically, we measured the accuracy of the Monte Carlo center election algorithm, and the success rate of routing with different settings, e.g., sampling rate, transmission range, etc.
- To study the trade-off between routing efficiency and conservation of sensor energy in sparse areas. Specifically, we measured path length and average node density for both density-aware routing strategy and greedy proximity-based one.

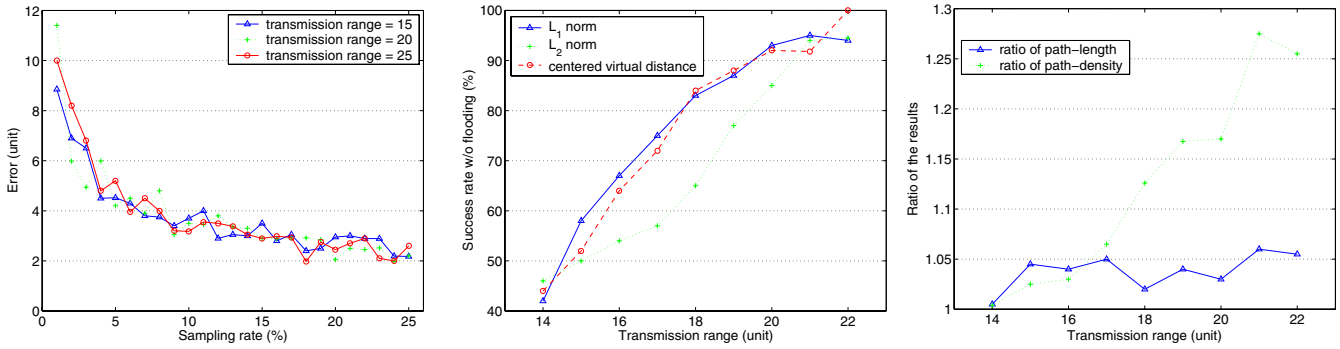
The simulated network consists of 20 groups, each of 80 sensor nodes, i.e., 1600 nodes in total, distributed in a square of length 500 units, with a circle hole of radius 100 in the center, as shown in Fig. 2(a). All the groups follow two-dimensional Gaussian distribution with σ = 100. The centers of groups are distributed on a perturbed grid. The communication graph used here is the unit disk graph over the nodes. Two nodes can communicate with each other directly if their distance is less than the transmission range. If not stated otherwise, the default setting will be: transmission range 20 units, sampling rate 5% and $\alpha = 0.35$. All the experiments are implemented in C++.

A. Accuracy of center election algorithm

We evaluated the accuracy of our Monte Carlo center election algorithm by measuring the average Euclidean distance between the centers of underlying distributions (true values) and the locations of elected center nodes for the 20 groups. Note that the lower bound of the error may not be zero, because of the discrepancy between probabilistic distribution and actual deployment. We ran the experiments with different settings of sampling rate and transmission range. The result is plotted in Fig. 5(a). One can notice that with sampling rate of 15% or higher, the error approaches the possible lower bound, no matter what transmission range is.

B. Success rate of routing without flooding

Our routing algorithm can always make progress across intermediate groups towards the destination, however it may get stuck in the final group due to local minimum, in which case, small scale flooding is necessary. The node density plays



(a) (b) (c)

Fig. 5. (a) Accuracy of the Monte Carlo center election algorithm versus the sampling rate. (b) Success rate of routing without flooding versus transmission range. (c) Ratio of the results (path-length, path-density) produced by density-aware routing and greedy proximity-based strategies, versus transmission range.

an important role in determining the rate of successful routing. Though our algorithm is designed with intension for densely distributed sensor network, it is very tolerant to sparse and non-evenly dense deployment. We ran the experiments with varying transmission range, which is in effect equivalent to changing the node density. For each setting, we measured the average percentage of successful routing out of 30 random tests. The result is shown in Fig. 5(b). It is clear that with transmission range above 20 units, our routing approach can achieve success rate near 100% regardless of the distance metric used.

C. Trade-off between efficiency and network lifetime

Density-aware routing scheme is designed to achieve good trade-off between routing efficiency and prolonged network lifetime. We compared the performance of our approach with that of a pure proximity-based implementation, by measuring the path length and path density, as discussed in the previous section. The ratio of the results produced by two approaches is plotted in Fig. 5(c). It is clear that with trivial extra cost on path length, our approach achieves considerable gain on path density. Also note that this trend becomes even more significant as transmission range increases, which implicates the fact that the selection of successor plays an important role in densely deployed sensor network.

VI. CONCLUSION

In this paper we present a novel addressing and routing scheme for wireless sensor networks. By taking advantage of deployment knowledge, we design a protocol that distributedly discovers the high-level topology of the field. Efficient routing is achieved as two sub-procedures, proactive path planning and reactive local routing. Moreover, our approach also takes consideration of node density information, and achieves a good balance between routing efficiency and energy conservation for indispensable nodes, which is especially important for non-evenly dense sensor networks.

This paper is only preliminary work on group-based routing, and there is plenty space for exploration. For example, the selection of local coordinate system is an important research problem, combining our location-free routing technique with location-based approaches to achieve better performance deserves to be explored, and adapting our routing approach to sensor networks with mobility is also worth further investigation.

REFERENCES

[1] W. Bryc. “The Normal Distribution: Characterizations With Applications”. Springer Verlag, 1995.

[2] P. Bahl and V. Padmanabhan. “RADAR: An in-building RF-based user location and tracking system”. In *Proc.* of *IEEE INFOCOM*, 2000.

[3] A. Caruso, S. Chessa, S. De and A. Urpi. “GPS Free Coordinate Assignment and Routing in Wireless Sensor Networks”. In *Proc.* of *IEEE INFOCOM* 2005.

[4] L. Fang, W. Du and P. Ning. “A Beacon-Less Location Discovery Scheme for Wireless Sensor Networks”. In *Proc.* of *IEEE INFOCOM* 2004.

[5] Q. Fang, J. Gao, L. Guibas, V. de Silva and L. Zhang. “GLIDER: Gradient Landmark-Based Distributed Routing for Sensor Networks”. In *Proc.* of *IEEE INFOCOM* 2005.

[6] Q. Fang, J. Gao and L. Guibas. “Landmark-Based Information Storage and Retrieval in Sensor Networks”. In *Proc.* of *IEEE INFOCOM* 2006.

[7] R. Fonseca, S. Ratnasamy, J. Zhao, C. Ee, D. Culler, S. Shenker and I. Stoica. “Beacon Vector Routing: Scalable Point-to-Point Routing in Wireless Sensornets”. In *Proc.* of *IEEE INFOCOM* 2005.

[8] W. Fung, D. Sun and J. Gehrke. “COUGAR: The Network is the Database”. In *Proc.* of *ACM SIGMOD*, 2002.

[9] J. Gao, L. Guibas, J. Hershberger, L. Zhang and A. Zhu. “Geometric spanner for routing in mobile networks”. In *Proc.* of *MobiHoc*, 2001.

[10] B. Karp and H. Kung. “GPSR: Greedy perimeter stateless routing for wireless networks”. In *Proc.* of *ACM MobiCom*, 2000.

[11] V. Lenders, M. May and B. Planner. ”Density-based vs. Proximity-based Anycast Routig for Mobile Networks”. In *Proc.* of *IEEE INFOCOM*, 2006.

[12] W. Liao, J. Sheu and Y. Tseng. “GRID: A fully location-aware routing protocol for mobile ad hoc networks”. *Telecommunication Systems*, vol. 18, no. 1-3 pp. 37-60, 2001.

[13] S. Madden, M.Franklin, J. Hellerstein and W.Hong. “Tag: a tiny aggregation service for ad-hoc sensor networks”. In *SIGOPS Oper. Syst. Rev.*, vol 36, no. SI, pp. 131-146, 2002.

[14] D. Niculescu. “Communication paradigms for sensor networks”. *IEEE Communications Magazine*, vol. 43, is. 3, pp. 116-122, 2005.

[15] D. Niculescu and B. Nath. “Ad hoc positioning systems (aps) using aoa”. In *Proc.* of *IEEE INFOCOM*, 2003.

[16] S. Ratnasamy, B. Karp, L. Yin, F. Yu, D. Estrin, R. Govindan and S. Shenker. “GHT: A geographic hash table for data-centric storage”. In *Proc.* of *WSNA*, 2002.

[17] A. Rao, S. Ratnasamy, C. Papadimitrious, S. Shenker and I. Stoica. “Geographic routing without location information”. In *Proc.* of *ACM MobiCom*, 2003.

[18] T. Wang, S. Hao, P. Wang and G. Peng. “Density-Aware Routing for Sensor Networks”. Technical Report, http://www.cs.ubc.ca/ğuasars/research, 2006.