Purposeful Mobility for Relaying and Surveillance in Mobile Ad Hoc Sensor Networks

Rajesh Rao, *Student Member, IEEE*, and George Kesidis, *Senior Member, IEEE*

Abstract—In this paper, we consider a mobile ad hoc sensor network. The mobility of the sensor nodes is *designed* with the cost of communication and mobility in mind along with consideration of the possible scanning tasks of the nodes. Our mobility algorithm is developed in the context of a distributed system where, for any single mobile node, only local information about associated energy costs is known. We use a distributed simulated annealing framework to govern the motion of the nodes and prove that, in a limiting sense, a global objective function comprising mobility and communication energy costs will be minimized. This paper concludes with a simulation study focusing on mobile sensors with dual roles of scanning and relaying higher priority tracking traffic from tracking nodes.

Index Terms—Sensor networks, MANET, mobility strategy, communication, energy-aware systems.

1 INTRODUCTION

TRADITIONAL mobile ad hoc networks (MANETs) typically treat node mobility as an uncontrolled factor. In sensor MANETs, the nodes have a communal surveillance (tracking/scanning) mission and mobility, in some cases, that can be *designed* to help achieve the mission. In addition, mobility can be used to provide logistical support by, for example, facilitating network connectivity and achieving better communication, in general, between the sensors and data repository (cache or larger database) or, in a real-time setting, the command-and-control entities of the network. Also, node mobility makes the network more robust against node failure events.

We consider the real-time, command-and-control context of a sensor MANET deployed in battlefield environment to perform surveillance tasks. Each node is a robot carrying one or more sensors. These sensors collect information and transmit it to a data sink: base-station (satellite up-link) or command-and-control center. The nodes are required to track any hostile targets they sense, perform local scans (explore local surrounding that are not covered by any other nodes), and forward data from neighboring nodes toward the base station.

The specific goal of communal-mission-oriented (i.e., “purposeful”) mobility is to decide where to move a node so that it can perform any one or all the tasks better. We assume that a node at any given time can be a tracking node or a scanning node. The data generated by the tracking

nodes is considered latency-critical since we are looking to provide detailed information on tracked targets in real time. The scanning node generates lower volume, nonlatency-critical data about its local surroundings. The scanning node also relays traffic, i.e. it forwards, in particular, latency-critical data toward the base station node. Other kinds of communication are possible in such a sensor MANET including that required for coordination of target tracking and overhead for communication route establishment and maintenance. In the somewhat more simplified setting of this paper, we target a single network “time-scale” and focus on scanning nodes moving to scan a new area and/or reduce the total transmission power used by the network for high-priority tracking traffic. We are interested in *distributed* mobility algorithms relying only on information local to the node.

For terrestrial vehicles (nodes), the cost of mobility may be high depending on their weight and on the environmental conditions (terrain). If we consider unmanned aerial vehicles (UAVs), there is a roughly fixed power cost to keep the UAV airborne. The power cost of motion for scanning and relaying (the focus of this paper) would be the additional cost needed to maneuver the UAV in the necessary directions. This cost may be relatively low compared to that required to keep the UAV airborne. For unmanned underwater vehicles (UUVs), the cost of motion may be significantly lower than that of terrestrial vehicles in certain environments. If there is a fixed power cost for necessary mobility, we can include it together with that of computation and communication-reception under one fixed cost π . The available energy of a node at any time $t > 0$ will then be

$$E_t = E_0 - \pi t - M_t - C_t,$$

where M_t is the cumulative energy required for additional motion and C_t is the cumulative energy required for communication-transmission.

• R. Rao is with the Department of Electrical Engineering, The Pennsylvania State University, 121 Electrical Engineering East, University Park, PA 16802. E-mail: rnr115@psu.edu.

• G. Kesidis is with the Department of Electrical Engineering and the Department of Computer Science and Engineering, The Pennsylvania State University, 121 Electrical Engineering East, University Park, PA 16802-2705. E-mail: kesidis@engr.psu.edu.

Manuscript received 15 Mar. 2004; revised 19 May 2004; accepted 26 May 2004.

For information on obtaining reprints of this article, please send e-mail to: tmc@computer.org, and reference IEEECS Log Number TMCSI-0083-0504.

Two cases are considered in this paper, both assuming statically positioned tracking nodes generating latency critical data that is forwarded by mobile “intermediate” nodes to the single data sink. In the first case, the intermediate nodes only relay the tracking information to the sink. The intermediate nodes move so that the total transmission power is reduced. For example, if a node is relaying a large volume of data between two nodes, it will obviously save energy in transmission if it is closer to them. The cost of motion to a chosen location will be amortized against the savings in communication energy at that location as predicted by the node (again, using only local information). To this optimization problem, we can apply a greedy approach to select the optimum position of nodes. This may result in a optimal solution locally, but could potentially give rise to suboptimal placement globally. To prevent this, we employ simulated annealing wherein a node, with a positive probability, accepts a “bad move” locally because the move could benefit the network globally in the longer run. This is explained in greater detail in Section 3. Note how the use of “randomized” motion is, at least in part, motivated by the distributed nature of the problem we have formulated. Alternative motivations for random motion of sensor nodes were articulated in [8].

In the second case, the intermediate nodes are assigned both scanning and relaying tasks. To reiterate, we assume that data volume generated by intermediate nodes is of lower priority and of negligible volume compared to the data from the tracking nodes. The goal here is to find optimal node paths to conserve power and to cover areas not explored by any nodes. An intermediate node could move either to save communication energy or to perform local scans. This mobility strategy is explained in greater detail in Section 4.

The remainder of the paper is organized as follows: A survey of related literature is given in Section 2. In Section 5, our simulation study is described. The paper concludes with a summary and discussion of future work in Section 6.

2 RELATED WORK

Issues of surveillance coverage and communication connectivity for random static positioning of sensors were explored in [5] and, more recently, in [13]. In [13], the nodes are active with certain probability with a given sensing and communication radius. They have derived results to prove connectivity, and coverage is maintained even if the probability of a node being active and communication radius are low. This may give the communication radius for coverage and connectivity, but only for a static network. It is not possible to extend this framework to include mobility as the nodes are assumed to be uniformly arranged.

Clearly, a basic motivation of node mobility is that the nodes are not deployed with sufficient density in the region under surveillance to make mobility of the nodes unnecessary. In this paper, we assume that the sensors deployed are somewhat sophisticated and costly so that very dense deployment is infeasible.

In [11], the effect of mobility on a position detection algorithm was considered. They suggested the use of hop-counts from reference nodes to find relative positions of all nodes. Nodes are moved to neighborhoods where accurate

information is not available. Mobility helps to increase accuracy of information regarding node positions, but does not help to find the best position for coverage or connectivity.

Flocking properties of platoons of UAVs were studied in [14]. Specifically, they explored local mobility laws that keep formation (velocity and heading).

In [8], the authors evaluate the distribution of the time until detection of a point-target under purely random (diffusion) mobility per node. Given an associated Bessel process describing the distance between any two given nodes, there also exist expressions for the distribution of the time between successive contact of any two nodes assuming each of their communication ranges is bounded, see [1, p. 207].

In [10], the authors look at navigating across a vehicle across a sensor grid. The nodes in the sensor interacts with the vehicle giving it local information about the terrain. The vehicle then decides where to move next.

In [16], the authors consider a scenario where mobility assists the nodes in sensor deployment. The goal is to maximize coverage while not compromising connectivity by intuitively enacting local repulsion of nodes (to minimize redundancy of coverage) along with long-range attraction of nodes so as not to compromise network connectivity. Zou and Chakrabarty and [17] and Heo and Varshney [6] also consider virtual forces between the nodes for sensor deployment. Again, the mobility assists only in the deployment of a static network.

Finally, simulated annealing mechanisms have been proposed in the past for other networking purposes. For example, in [15], a (centralized) simulated annealing algorithm was used for clusterhead selection based on weights assigned to nodes.

3 DETERMINISTIC AND RANDOM MOBILITY FOR RELAY NETWORKING

In this section, we assume a single task per node. For example, in response to target detection, certain nodes (proximal to the target) are assigned logistical target-tracking tasks while others are assigned tasks supporting communication. We focus herein on mobility for the latter category of nodes and, for those nodes, state that a goal of node *mobility* is to maximize the life time of the MANET and, at the same time, perform the required relaying tasks satisfactorily. Our specific objective is to incrementally find the node positions that minimize the total required transmission power for all the active flows in the MANET while suitably “penalizing” for the energy cost of motion in order to find these positions.

For a node to move from one position to another, there must be a significant resulting reduction in communication power compared to the power consumed for motion. This would vary significantly depending on the environment of the moving vehicle operates in. For example, the relative cost for UAVs will be significantly less than UUVs, which will be significantly less than terrestrial vehicles. In the following, we assume that nodes make such decisions based only on local information (traffic and neighbor positions) as appropriate for a highly decentralized and distributed sensor MANET. We will devise a distributed mobility strategy based on the simulated annealing algorithm, see, e.g., [9]. The randomness

introduced in the strategy will allow the sensor MANET to avoid positions that are suboptimal local minima of its objective.

3.1 Basic Network Model Assumptions and a “Greedy” Mobility Strategy

We need to define the following terms for our problem formulation:

- N is the number of intermediate relay nodes.
- F is the number of flows each of constant rate λ packets/s (fixed length packets assumed herein).
- x is a vector of the positions of the intermediate relay nodes (so, in 3-dimensions, x is actually an $N \times 3$ matrix).
- r is the set of F routes (each assigned to one flow) where a route through the network is determined by a series of nodes beginning with a source and ending with a data sink.
- $V(x, r)$ is the total power required from the network to transmit the F flows using routes r when the intermediate nodes are in positions x ; the optimal choice of routes at position x is

$$R(x) \equiv \arg \min_{r \in \mathcal{R}(x)} V(x, r),$$

where $\mathcal{R}(x)$ is the set of feasible routes connecting those nodes when in positions x .

The quantity $R(x)$ is the objective of a distributed routing algorithm (like Bellman-Ford [2]) and its determination is assumed to occur on a much faster time scale than that of the mobility of the nodes. Further, assume that all nodes have an associated clock cycling every T seconds (clocks are not necessarily synchronized). Once every cycle, a node decides with probability p whether it should attempt to move. Under a deterministic “greedy” mobility strategy, node k at position x_k will move to position z that minimizes

$$\begin{aligned} V((x_{-k}; z), R(x)) - V(x, R(x)) + c|z - x_k|/T \\ \equiv \Delta_k V(x, z) + c|z - x_k|/T, \end{aligned} \quad (1)$$

where $(x_{-k}; z)$ represents the vector x with x_k replaced by z , and $c|z - x_k|$ represents the amount of energy required for the move that we have chosen to amortize over a clock cycle-time (c is a fixed parameter of the assumed “constant” terrain). Movement according to (1) may be velocity v constrained, i.e.,

$$|z - x_k| \leq vT.$$

For a simple illustrative example, consider a relay node k that forwards two flows from its tributary nodes i and j to node l . Suppose that the power required to transmit over distance d (again, at rate λ packets/s) is given by Kd^α Watts, where K is a constant and $\alpha \geq 2$ is a transmission attenuation factor [4]. So, for this example,

$$\begin{aligned} \Delta_k V(x, z) = K[|z - x_i|^\alpha + |z - x_j|^\alpha + 2|z - x_l|^\alpha - |x_k - x_i|^\alpha \\ - |x_k - x_j|^\alpha - 2|x_k - x_l|^\alpha]. \end{aligned} \quad (2)$$

A basic assumption herein is that the quantity in (1) is computable by node k requiring, in particular, knowledge of the location of its neighbors [12]. Note that what makes

this “distributed” computation of $\Delta_k V(x, z)$ is the fact that V is an *additive* function of the transmission power required at each node. The existing routes (at x) are used in the term $V((x_{-k}; z), R(x))$ because, in this distributed setting, the node k does not know the consequences its move will have on the routes. When multiple nodes can move simultaneously, the uncertainty in the benefit of a move is significantly larger; to reduce the likelihood of this, one may set $p = 1/N$ for this case of static sources and sinks.

3.2 Mobility by Distributed Annealing

This greedy method may converge to a “suboptimal” solution because: $V(x, R(x))$ may have local minima; simultaneous motion of multiple nodes; and/or suboptimal local movement, i.e.,

$$\begin{aligned} \min_z \Delta_k V(x, z) + c|z - x_k|/T \geq \\ \min_z V((x_{-k}; z), R((x_{-k}; z))) \\ - V(x, R(x)) + c|z - x_k|/T. \end{aligned}$$

So, we propose a randomized motion on a lattice resulting in a kind of distributed simulated annealing algorithm. Motion is restricted to a lattice and a node k (currently at x_k) selects a neighboring position z at random and accepts the move to z according to a “heat bath” probability (5)). Many other kinds of motion randomization could be used [8]. but we chose annealing on a lattice because it is tractable in the following sense: Assuming no simultaneous motion of nodes, we show in the following theorem that limit of this annealing motion tends to the (assumed unique) state x that minimizes

$$U(x) \equiv V(x, R(x)) + cT^{-1} \sum_{k=1}^N |x_k| \quad (3)$$

$$\equiv V(x, R(x)) + cT^{-1} \|x\|. \quad (4)$$

In this function, we clearly see the total cost of transmission power combined with the amortized cost of motion to positions x from the origin over a constant terrain.

Consider the framework of, e.g., [9] with potential function (Hamiltonian) $U(x)$ given by (3) over all states $x \in D$, where D is a lattice. We can define a time-reversible discrete-time annealing Markov chain on D with associated transition-probability matrix (TPM) P and stationary distribution π . More specifically, consider an aperiodic, irreducible, and time-reversible Markov chain with TPM Q and stationary distribution μ , i.e., detailed balance holds: $\mu_x Q_{x,y} = \mu_y Q_{y,x}$ for all states $x, y \in D$ and $Q_{x,y} > 0$ implies that x and y are neighboring points in D , e.g., $y = (x_{-k}, z)$ for some k and z as above. Define the annealing chain using the heat bath acceptance probability rule: for states $x \neq y$,

$$P_{x,y} \equiv Q_{x,y} \min\{1, \exp(\beta(U(y) - U(x)))\},$$

where $\beta > 0$ is interpreted as inverse temperature and, for our purposes herein, a constant. So, the TPM P inherits aperiodicity and irreducibility from Q . The TPM is also time-reversible with *Gibbs* stationary distribution:

$$\pi_x = \frac{\mu_x e^{-\beta U(x)}}{Z_\beta},$$

where Z_β is the normalizing constant (partition function).

Now, define a TPM for the distributed annealing process:

$$\hat{P}_{x,y} \equiv Q_{x,y} \min\{1, \exp(\beta[V(y, R(x)) - V(x, R(x)) + c||y - x||/T])\}. \quad (5)$$

The TPM $\hat{P}$ continues to be irreducible and aperiodic, thereby yielding a unique stationary distribution $\hat{\pi}$ [3], but is no longer time-reversible.

Lemma 1. $P_{x,y} \geq \hat{P}_{x,y}$ for all $x \neq y$, and $P_{x,x} \leq \hat{P}_{x,x}$ for all x .

Proof. By the definition of R and the triangle inequality,

$$\begin{aligned} V(y, R(x)) - V(x, R(x)) + c||y - x||/T \\ \geq V(y, R(y)) + c||y||/T - [V(x, R(x)) + c||x||/T] \\ = U(y) - U(x). \end{aligned}$$

The first statement of the lemma directly follows from the definitions of P and $\hat{P}$. The second statement is an immediate corollary of the first because both P and $\hat{P}$ are row-stochastic matrices. $\square$

Now, since π is Gibbs,

$$\lim_{\beta \rightarrow \infty} \pi_x(\beta) = 0 \text{ for all } x \notin \Omega \equiv \arg \min_{x \in D} U(x), \quad (6)$$

where we have explicitly shown the dependence of π on β ($\beta \rightarrow \infty$ is interpreted as “cooling”). The following result states that the distributed annealing chain, $\hat{P}$, also has a stationary distribution with this “Gibbs like” property.

Theorem 1. If Ω is a singleton set, i.e., $\Omega \equiv \{x^*\}$, then

$$\lim_{\beta \rightarrow \infty} \hat{\pi}(\beta) = \mathbf{1}^{x^*},$$

where $\mathbf{1}_y^{x^*} = 0$ if $y \neq x^*$ and $\mathbf{1}_{x^*}^{x^*} = 1$.

Proof. First, note that

$$[(\mathbf{1}^{x^*})' \hat{P}(\beta)]_y = \hat{P}_{x^*,y}(\beta).$$

If $y \neq x^*$, then by Lemma 1,

$$\hat{P}_{x^*,y}(\beta) \leq P_{x^*,y}(\beta) \rightarrow 0 \text{ as } \beta \rightarrow \infty.$$

Otherwise, if $y = x^*$, then again by Lemma 1,

$$\hat{P}_{x^*,x^*}(\beta) \geq P_{x^*,x^*}(\beta) \rightarrow 1 \text{ as } \beta \rightarrow \infty.$$

Therefore,

$$\lim_{\beta \rightarrow \infty} (\mathbf{1}^{x^*})' \hat{P}(\beta) = (\mathbf{1}^{x^*})'. \quad (7)$$

Now, recall that $\hat{\pi}(\beta)$ is the unique solution to

$$\begin{aligned} \hat{\pi}(\beta)'(I - \hat{P}(\beta)) &= 0 \\ \text{and } \hat{\pi}(\beta)' \mathbf{1}^D &= 1, \end{aligned}$$

where $\mathbf{1}^D$ is a vector all of whose entries are 1. Let $\hat{V}(\beta)$ be the matrix obtained by replacing a column of $I - \hat{P}(\beta)$, say, column n , by $\mathbf{1}^D$. Thus, $\hat{\pi}(\beta)$ is the unique solution to

$$\hat{\pi}(\beta)' \hat{V}(\beta) = (\mathbf{1}^n)'. \quad (8)$$

Uniqueness implies that the null space of $\hat{V}(\beta)$ must be just the zero vector; this, in turn, implies that $\hat{V}(\beta)$ is nonsingular giving, for all $\beta > 0$:

$$\hat{\pi}(\beta)' = (\mathbf{1}^n)' [\hat{V}(\beta)]^{-1}.$$

Beginning with (7) and using the same argument,

$$\lim_{\beta \rightarrow \infty} (\mathbf{1}^n)' [\hat{V}(\beta)]^{-1} = (\mathbf{1}^{x^*})'.$$

The theorem statement follows from the last two equations. $\square$

A straight-forward extension to this theorem (using (6)) follows for optimal sets Ω in which no two states are directly connected by the TPM Q .

In summary, we have demonstrated that randomized annealing motion of the sensor nodes, distributed in the sense that only local information is used, nevertheless retains a Gibbs-like property, i.e., a natural composite utility of communication and mobility costs (3) is minimized as the temperature β^{-1} cools.

4 DUAL TASKING: SCANNING AND RELAYING

In this section, we look at combining the two tasks of scanning and relaying for the intermediate nodes in greater detail. The goal of the scanning task is to move to a location in the surveillance area not visited before or not visited by a scanning node in a long time. To quantify this, we partition the surveillance area with a grid. A node selects a “scanning move” with probability p_s and “relaying move” with probability $p_r = p - p_s$, where $0 < p_s, p_r < 1$.

A simple method of scanning involves maintenance of a “taboo list” of, say, the last 10 points visited by the node. When considering a scanning move, points on the taboo list are excluded and the remaining choices are chosen uniformly at random. Alternatively, the taboo list can also maintain the *time* of the last visit so that the list could be implemented as a sliding time-window.

For both of the approaches above, the taboo lists or lists of time-stamps can be exchanged by neighboring nodes and merged to create a more up-to-date table (at each node), where we note that the latter will require some kind of time time-synchronization among the nodes.

5 SIMULATION STUDY

We considered a MANET with seven nodes, including four mobile relays, operating within a 40m $\times$ 40m square area (for the following simulations, the units of distance can be scaled-up by suitable modification of the following mobility and communication parameters). We assumed there are two stationary (immobile) source (tracking) nodes and a single stationary data-sink (base station) node. Source nodes generated data at a constant bit rate of 100kbps with 50-byte packets.

We chose the following communication and mobility parameters for our simulation study. The relative motion constant c of the global utility function (3) was assumed to be determined by the figure 50mJ/m; i.e., a node weighing 1kg required about 5mJ to move a distance of 0.1m. The

Fig. 1. Total transmission power over time for different fixed β .

value of the parameter K from (2), determining communication power required to transmit a packet over a distance of 1m, was assumed to be $1mW$. Also, for this equation, the communication attenuation parameter was assumed to be $\alpha = 2.5$. Finally, the intermediate nodes involved in forwarding traffic from sources to sink made a movement decision every $T = 10$ seconds.

Initially, the positions $x(0)$ of the nodes are chosen independently and uniformly at random in the area under consideration. In the simulation, we also assume all active relay nodes move at all times, i.e., $p = 1$ instead of $p = 1/N$ as advised in the end of Section 3.1.

A transmission power-based (distributed Bellman-Ford with d^α as metric) routing algorithm was assumed to be in effect determining the routes $R(x)$ at node-positions x (again, assumed to operate at a time-scale much faster than that of node movement, T). As we are using power-based routing algorithm, we assume nodes can communicate with all nodes in the given region. A node wishing to communicate with a farther node can do so by increasing its transmission power.

Finally, from each set of simulation trials, we determined an empirical mean and 95 percent confidence interval; in the following graphs, the confidence interval is indicated by a vertical bar centered at the mean.

5.1 Single Task per Node

In this set of simulations, we assumed that the intermediate nodes have a single task, i.e., that of relaying source-node tracking-data transmissions to the sink-node. That is, the relay nodes did not generate any scanning data of their own.

In Fig. 1, we plot the total transmission power of the network over time for different values of the β parameter in the annealing algorithm (i.e., the inverse temperature). Note that β was a fixed constant for each simulation run. As β increased (temperature decreased or cooled), note that the variance in total transmission power decreased. For lower values of β , the nodes accepted “bad” moves with higher probability, hence the higher variance in total transmission power. The increased variance at the beginning of each set of simulation trials was due to the randomly chosen initial positions for each simulation run. This variance reduces as the nodes move closer to the optimal position. Since we average over different initial positions, the reduction in total transmission power might not appear significant. But, for cases where

nodes have a bad initial position, we observed a reduction in total transmission power by as much as a factor of 3. The β value also controls the rate of convergence. For larger β , the nodes move to an optimal position more quickly. We note this difference in the total transmission plot for $\beta = 50$ and $\beta = 500$. For $\beta = 50$, the total transmission power reaches the optimal value after 700s and continues to change around the optimal value. For $\beta = 500$, the total transmission power reaches the optimal value after 450s and remains relatively unaltered.

In Fig. 2, we “cooled” the temperature during each simulation run in order to trap the nodes into optimal positions from the perspective of communication power. More specifically, every 10s, β was increased in increments of 20 from an initial value of 200. As the β increases, the variance in the transmission power predictably decreased. Such a cooling schedule makes sense in the context of constant bit-rate and stationary source nodes, stationary data sinks, and with no scanning motion, but would not make sense in a more dynamic networking environment, c.f., Sections 5.2 and 6.

Fig. 3 shows the initial and final position of the intermediate nodes of a representative sample path of a single simulation run. Note how the relay nodes have basically formed a line between the sources and sink to reduce transmission distance.

Fig. 4 shows the transmission energy saved compared to the energy spent in moving from the initial node-positions,

Fig. 2. Total transmission power when β increased dynamically (cooling).

Fig. 3. Initial and final node positions.

for different values of β . The energy saved in transmission was on the order of a few tens of Joules, while the energy spent in moving the nodes was of the order of few hundred mJ clearly demonstrating the worth of mobility in the context of our selected parameters.

For large β , mobility is typically restricted to moves that deterministically reduce transmission energy. The result is both a reduction of transmission energy and a small amount of energy is spent on mobility, but poor local minimas may occur. Under the annealing policy, as the value of β decreases, the nodes have greater freedom to move. This ultimately reduces the energy saved in transmission because poor local minima are avoided as the nodes make more “bad” moves to better explore the space of relay node-positions (i.e., a greater breadth of search).

5.2 Dual Tasking per Node

In this set of simulations, we assumed that the intermediate nodes had both a scanning and relaying function, as described in Section 4. The simple method involving a taboo list of the last 10 points visited by the node was simulated. Taboo lists of neighboring nodes were not exchanged. Finally, we assumed that the transmission energy for scanning (passive surveillance) traffic was negligible compared to that of the tracking traffic and the former was not accounted for.

For two values of the scanning-decision probability parameter, $p_s \in \{0.4, 0.6\}$, the communication energy is

plotted in Fig. 5. One can also compare with the second graph of Fig. 1 in which $p_s = 0$. Note that the effect of increasing p_s (i.e., a greater propensity for scanning moves) has an effect on communication energy similar to that of increasing temperature for singly tasked (relay) nodes as indicated in Fig. 1. Of course, the advantage of increasing p_s is that the nodes cover (scan) more of the area under surveillance. Defining coverage as the total number of *different* points visited by all of the scan-relay intermediate nodes over a sliding time-window of 20 seconds, the $p_s = 0.6$ trials depicted in Fig. 5 achieved 25 percent more coverage on average than the trials using $p_s = 0.4$. Indeed, both p_s and the temperature β^{-1} affect coverage which significantly increased with decreasing β for the trials of Fig. 1.

6 DISCUSSION AND FUTURE WORK

We demonstrated that motion based on our *distributed* annealing method results in the maximization of the desired objective (2) accounting for both total transmission power and the energy required for motion. When assuming only a relaying task for intermediate nodes and stationary tracking nodes and data sink, the annealing algorithm can be allowed to “cool” (β increased) to trap the relay nodes in optimal positions. However, if the tracking nodes themselves move or the tracking tasking is dynamic, cooling would make the relay network less responsive to this change. Such change is part of more general “volatility” in

Fig. 4. Mobility and transmission energy.

Fig. 5. Total transmission power over time.

networking conditions that may be experienced by the relay nodes. When such conditions change slowly, an alternate cooling (over a period of stable conditions) and heating up (over a period of volatile conditions) of the annealing algorithm may be beneficial. During periods of sustained change, there may be no advantage to cooling at all. Clearly, if an additional scanning task was added, cooling may make little sense as it would tend to cluster nodes about their optimal positions for relaying. In our algorithm, node *responsiveness* is p/T (the average number of moves per second). Sources of network “volatility” include: finite-lifetime batteries, traffic, source/sink node mobility, changing environmental conditions affecting the channel and terrain, enemy activity targeting the network itself, etc. In general, local perceptions of increasing volatility require increased node responsiveness; i.e., a node’s p -value could increase (more likely to move) and/or its clock cycle-time T could decrease. Such p/T -adaptation also results in smoother motion. Increased responsiveness may, however, result in annealing motion based on cruder estimates of the change in the objective function, U , due to, e.g., more simultaneous movement, and a convergence of time-scales for routing (to determine $R(x)$) and mobility.

We are currently exploring our distributed annealing framework for motion together with dynamic node responsiveness for volatile network conditions. Also, we are considering more heterogeneous terrain and networking contexts. Finally, we are developing suitable dual-priority routing algorithms in order to more accurately manage the energy required for joint communication of tracking (high priority) and scanning (low priority) traffic, particularly for volatile network conditions [7].

ACKNOWLEDGMENTS

This research was funded in part by a US National Science Foundation grant ITR-0312558 and by the US Defense Advanced Research Projects Agency (DARPA), and administered by the US Army Research Office (ARO) under ESP MURI Award No. DAAD19-01-1-0504. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the DARPA or the ARO.

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Rajesh Rao received the bachelor's degree from BMS College of Engineering, Bangalore University. He received the MS degree from Pennsylvania State University in electrical engineering. He is currently a PhD student with Dr. George Kesidis at Pennsylvania State University. His area of research is in mobile ad hoc networks and includes energy efficient routing, and mobility management of nodes. He is a student member of the IEEE.

George Kesidis received the MS and PhD degrees in electrical engineering and computer science from UC Berkeley in 1990 and 1992, respectively. He was a professor in the Electrical and Computer Engineering Department at the University of Waterloo, Canada, from 1992 to 2000. Since April 2000, he has been an associate professor in both the Electrical Engineering and Computer Science and Engineering Departments at the Pennsylvania State University. In 1999, he took a sabbatical with Nortel Networks, Ottawa. In 2001, he was a part-time member of the technical staff at Mahi Networks. Professor Kesidis's current funded projects include sensors networks, network economics, and cyber security. He is on the technical program committees of 2005 IEEE INFOCOM, ICC, and GLOBECOM, and will be the TPC cochair of 2007 INFOCOM. He is a senior member of the IEEE.

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