Swarm intelligence based surveillance protocol in sensor network with mobile supervisors

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***Abstract*— This paper addresses the surveillance problem using sensor networks with mobile sinks. Sensors' low computational capabilities and limited energy motivate our design of a swarm intelligence based, energy aware protocol, SSP, to route data to a mobile destination. Using the swarm agent technique to integrate nodes' residual energy as a metric for the route selection, SSP prolongs the network lifetime by evenly balancing residual energy across nodes and minimizing the protocol's overhead. The protocol scales well. Simulation results show that SSP outperforms similar protocols that are previously proposed.**

I. INTRODUCTION

With recent advances in device fabrication technology, economical deployment of large scale sensor networks, capable of pervasive monitoring and control of physical systems has become possible. Sensor networks can be deployed, for example, for surveillance of forests or civilian areas. In this paper we present a swarm intelligence based surveillance protocol using sensor networks with mobile supervisors. Supervisors are actually sinks that issue queries to sensors under its control or collects data from them. Supervisors, which can be forest rangers or policemen respectively in the two scenarios mentioned above, do not have to stay static or rely on base stations so that sensors can reach them when alert data emerge. In these scenarios, which reflect the scenarios of interest in this paper, most of the sensors stay static while supervisors are mobile. The problem of interest is: *how should the static sources report their data to the mobile supervisors so that network and the individual sensor's lifetime is maximized?* To address this issue, we present an on-line, energy aware sensor network surveillance protocol motivated by swarm intelligence theory(which we call SSP) to keep the mobile supervisors informed timely with alert data to carry out surveillance of the covered area.

The constant and unpredictable changes in the supervisor's location pose the major challenge for design of the surveillance protocol: *how should each data source deliver their report to the mobile supervisors efficiently?* [1] and [2] present protocols that aiming at information disseminating with the network lifetime maximized. However, they desire full knowledge of traffic demands. In [4], [5] "maximizing network lifetime" is taken as the objective and online algorithms are developed for static networks to route the data. The similar offline algorithm of [6] deals with static or slowly changing dynamic networks.

Most of the aforementioned routing protocols assume knowledge of the destination's identifier-based address. In the mobile sink scenario, frequently updating all sensors with supervisors' current location leads to significant overheads. Recent literature suggests several alternative approaches. Directed diffusion [10] routes data based on data interests periodically broadcasted by the sink. Certain paths for a given source are reinforced by the sink based on previously received data from the source. The fact that once the sink moves the reinforced paths are not valid anymore makes the scheme ineligible for accommodating high level of sink dynamics. A two-tier approach for data dissemination (TTDD) is proposed in [3] wherein each source forms a grid like path to the sink. However, aside from being energy unaware, the communication and state overhead associated with maintaining these routes degrade the protocol's scalability and ability to maximize network lifetime. In addition, all data to the sink/supervisor are relayed through the primary and immediate agents, which introduces central points of failure.

With the specific goal of maximizing the network or sensor lifetime in the mobile supervisor scenarios, this paper presents a protocol based on the concept of swarm intelligence [9]. Introducing of swarm intelligence techniques exempts individual sensors from possessing much intelligence or cooperating with each other tightly. Each of them follows simple rules and by their collective behavior the optimum is achieved. Our protocol ensures that supervisors are kept updated with information from data sources in an energy efficient and balanced manner to prolong the network lifetime.

The proposed protocol performs very well as far as the network lifetime, reliability, adaptability to network dynamics are concerned. It also achieves scalability. These properties of the protocol are verified using extensive simulations. Simulations also show that SSP outperforms even an ideal realization of the protocol (TTDD) proposed in [3].

The rest of the paper is organized as follows: background information and the SSP protocol are elaborated upon in Section II and Section III respectively. Section IV analyzes the proposed protocol. The simulation results are presented in Section V and conclusion in Section VI.

II. BACKGROUND AND DEFINITIONS

A. Assumptions and Terminology

In this section we list the assumptions made in this paper and define the terminology. Following are assumptions:

1) No prior knowledge about supervisors' mobility characteristics is available.

2) All sensors in the network are potential sources. No prior knowledge about source data generation characteristics is available.

These assumptions reflect the conditions in most realistic deployment scenarios and are necessary to ensure that the developed protocol is practical. Following are some definitions that will be used throughout this paper:

- **Lifetime** of the network is defined as the time till the first sensor in the network dies.
- **Downstream and Upstream** Downstream is defined as "to-the-supervisor" direction, while upstream refers to the opposite.
- **The Shortest Path** Suppose between a given source and destination there exist n paths, which we denote as $p_j, j \in 1, 2, \cdots, n$. The residual energy of the kth sensor v_j^k on path p_j is denoted by $e_j^k, k \in 1, 2, \cdots, h_j$, where h_j is the hop count on path p_j. Max-min routing chooses the path p_x where:

$$x = \arg\max_{j \in 1,2,\cdots n} \min_{k \in 1,2,\cdots,h_j} e_j^k \tag{1}$$

  i.e. it chooses the path which contains the sensor with the highest minimum residual energy.
- **Gradient** of a sensor indicates its next hop neighbor on its shortest path leading to the supervisor.

Note that other shortest path definitions are proposed in literature [4], [1], [5]. Our shortest path definition excels in that it involves less parameter tuning and has a far lower algorithm complexity.

III. SSP: THE SENSOR NETWORK SURVEILLANCE PROTOCOL

Supervisors' mobility brings up critical issues to each data source: where should the data be delivered? How to fulfill this energy-wise efficiently? In this section we address these issues and present our protocol, SSP, which is motivated by swarm intelligence theory that argues a set of simple rules can be designed for low intelligence agents such that by following the rules their collective behavior can achieve the optimum. In following sections we present rules designed for both supervisors and sensors. For ease of illustration, we first start with the case of a single supervisor in the network. Multiple supervisors scenario will be addressed later.

A. Rules of the Supervisor

The supervisor's mobility makes possession of accurate information about its locations at each data source at all times rather difficult considering the scalability issue and energy limitation. To ensure reliable data delivery in the presence of partial or outdated information at the data origins, we introduce swarm agent to distributively set up and update for each sensor the gradient pointing to the downstream neighbor on its shortest path leading to the supervisor. The swarm agent is advertised by the supervisor only when it loses contact with some of its one hop neighbors. Data from the sources reach the supervisor by taking the path marked out by the gradient at each sensor. Each swarm agent is identified by its sequence number and consists of two very short packets, the *precursor* and the *follower*. The supervisor advertises its swarm agent to its current neighbors when losing contact with one or more of it neighbors or at certain frequency, which will be addressed later.

B. Rules of Individual Sensor

Each sensor maintains the latest swarm agent's sequence number, denoted as N here. The protocol is event-driven and we define 3 major events that occur at sensors as follows:

- ROP(receive of *precursor*) Upon receiving of a *precursor* with the sequence number bigger than N, a sensor forwards it to all it neighbors and starts a timer with value T defined as:

$$T = 2 - E_r$$

  where e_r is the remaining energy of the sensor. Note that that the function above for calculating T is just an example. Realization of our scheme does not depend on any specific function as long as it is monotonously decreasing with certain bounds. A received swarm agent with out-of-order sequence number will simply gets dropped.
- ROF(receive of *follower*) If a *follower* is first received and has the same sequence number as the last *precursor* that the sensor previously receives, it will be forwarded to the sensor's neighbor upon expiration of its timer mentioned above. Duplicates of the *follower* are dropped without any further action. Most importantly, the sensor updates its shortest path gradient pointing to the sensor that the first *follower* comes from.
- ROM(receive of message) The message will be forwarded to the neighbor that the sensor's gradient is pointing to.

C. An Example

In this section we examine how the rules described above enable the mobile supervisor to stay notified with data reports from source sensors in an energy efficient manner. Take figure 1 as the example topology. Sensor 4 will be taken as an example to show how it can keep in touch with the mobile supervisor via setting up the shortest path in between using the light-weight swarm agent. For ease of explanation, we omit transmission and queueing delays, which will be addressed later. In figure 1 two metrics are associated with each sensor, its remaining energy(denoted by the number outside of the parenthesis) and timer (denoted by the number inside the parenthesis).

The procedure of how SSP marks out the shortest path is shown in figure 2:

1) At time 0 the supervisor sends out the swarm agent, including a *precursor* and a *follower*. Since the *precursor* simply cuts through the network, all sensors, including sensor 4, will receive the *precursor* at time 0; Sensor 1 and 6 set their gradients to the supervisor directly;
2) Node 1's timer expires at time 1.2, and the *follower* is sent out;
3) Node 2 receives the *follower* at time 1.2 and sends it out at time 1.5 when its timer expires;

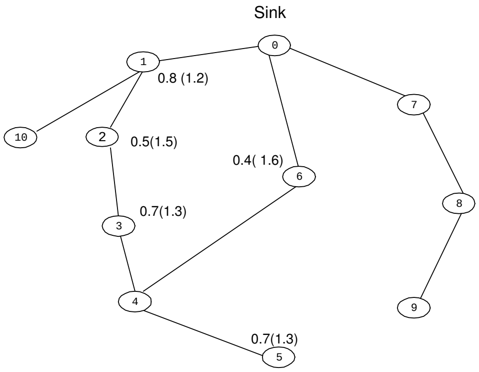

Fig. 1. Example: using swarm agent to update the shortest path.

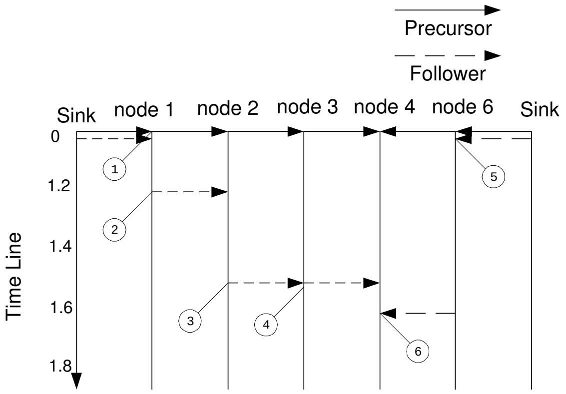

Fig. 2. Propagation of the *precursor* and *follower*.

4) Node 3's timer has already timed out when it receives the *follower* at time 1.5 and thus forwards it immediately. The *follower* reaches node 4 at time 1.5;
5) Node 6 receives the *follower* at time 0;
6) Node 6 sends out the *follower* at time 1.6 when its timer expires. Node 4 gets a second copy of the *follower* from node 6 at time 1.6 and it is simply dropped.

The swarm agent consists of two very short packets, whose typical one-hop transmission delay would be less than 1ms in typical MAC protocols [11]. If we bound the timer's minimum value as 1s, it will take 1000 hops for the accumulative transmission delay to reach the magnitude of the timer's value.

D. Multiple Supervisors Scenario

When multiple supervisors are present in a network, we define a sensor's *leading supervisor* as the supervisor that the sensor reports to. A sensor's *backup supervisor* is defined as the supervisor that the sensor is able to report to when the leading supervisor becomes unavailable. Note that a sensor can have more than one *back supervisors*.

Two different ways of supervision can be applied based on different network scales:

1) **Networks of large scale** The supervised area can be pre-divided into sub-regions with one supervisor in each of them. An example of the application scenario is a policeman patrolling in the areas that he is responsible for; In this case the swarm agent from each supervisor will only traverse sensors located in the area that the supervisor belongs to.
2) **Networks of small scale** Each supervisor can move liberally within the whole supervised area. Its swarm agent will also traverse the whole network. In this case each sensor will choose the supervisor that is the least hops away. The route to this supervisor will still be the shortest path defined previously.

These two schemes can be applied collaboratively in the same network, in which case each sub-area is covered by multiple supervisors.

IV. ANALYSIS OF SSP

A. Validity of the Shortest Path

Theorem 1: When MAC and other delays are negligible compared to the swarm agent's timer, paths to the sink specified by Eqn. (1) are accurately marked out by the swarm agent.

Proof: Consider an arbitrary node v with n paths to the sink which form a set $P = \{p_i | i \in 1, 2 \cdots n\}$. At time t the sink sends out a swarm agent that consists of a *precursor* and a *follower*. Define a mapping function:

$$t_v = M(e_v) \tag{2}$$

where $M(e_v)$ can be any bounded and monotonous decreasing function, where e_v is the residual energy of node v. t_v gives the initial value of node v's timer for the swarm agent. The swarm agent traveling along path p_j is also attached with an "agent timer", T_j, with initial value 0 when advertised from the sink. Let v_j^k denote the k-th hop on path p_j with initial energy e_j^k and timer t_j^k. As the swarm agent passes through this node, the agent timer, denoted as T_j^k, will be updated as:

$$T_j^k = \max\{T_j^{k-1}, t_j^k\} = \max\{T_j^{k-1}, M(e_j^k)\}$$

The swarm agent will be re-advertised by node v_j^k when T_j^k expires. Thus, finally node v will receive from path p_j a swarm agent with attached agent timer of value:

$$T_j = \max_{1 \le k \le h_j} M(e_j^k)$$

where h_j is the total hop count along path p_j. Now consider that node v receives swarm agents from n different paths. It is easy to see that an agent with a shorter "agent timer" always arrives earlier. From the monotonous decreasing nature of the mapping function (2), agent timer of the first arriving swarm agent is T_x where:

$$x = \arg\min_{1 \le j \le n} T_j = \arg\max_{1 \le j \le n} \min_{1 \le k \le h_j} e_j^k \tag{3}$$

The equation above is exactly the same as Eqn. (1) which defines the shortest path thereby proving the theorem. ■

B. Swarm Agent Frequency

In this section, we determine the update frequency required to ensure that the probability that the sink loses contact with any of the sensors currently in its range after t units of time is less than an arbitrary constant β, $0 < \beta < 1$.

For our analysis, we assume that the sink's mobility is governed by a two dimensional random walk. After every τ units of time, the sink randomly chooses an angle θ, distributed uniformly over $(0, 2\pi)$ and moves a distance d along that direction. After a random amount of time t (which for ease of derivations is assumed to be an integral multiple of τ), the sink moves a distance $R(t)$. We first establish the distribution of $R(t)$.

Claim 1: If $t/\tau \geq \sqrt[3]{\frac{3r^4}{16\epsilon d^4}}$ then Prob$\{R(t) \leq r\}$ follows a Rayleigh distribution with parameter $nd^2/2$.

Proof: In an interval t, the sink changes its direction $n = t/\tau$ times and its final position is the sum of n random phasors of magnitude d. The x and y coordinates of this position are given by: $X_n = \sum_{i=1}^{n} d\cos\theta_i$ and $Y_n = \sum_{i=1}^{n} d\sin\theta_i$. As n becomes large, the use of central limit theorem implies that the distribution of X_n and Y_n become Gaussian with mean 0 and variance $nd^2/2$. Transforming the joint distribution of X_n and Y_n to polar coordinates then gives the pdf of $R(t)$. In the case where n may not be large enough to satisfy the central limit theorem, in [12] it is shown that the pdf of $R(t)$ is given by

$$p(r) = \frac{2re^{\frac{-r^2}{\alpha}}}{\alpha}\left[1+\frac{3}{8n}\left(\frac{E[d^4]}{E[d^2]^2}-2\right)\left(\frac{r^4}{2\alpha^2}-\frac{2r^2}{\alpha}+1\right)\right] \qquad (4)$$

where $\alpha = nE[d^2]$. Note that the term outside the square braces is the Rayleigh distribution and thus for $p(r)$ to be within ϵ of this distribution

$$\left|\frac{3}{8n}\left(\frac{E[d^4]}{E[d^2]^2}-2\right)\left(\frac{r^4}{2\alpha^2}-\frac{2r^2}{\alpha}+1\right)\right| \leq \epsilon \qquad (5)$$

For our random walk model where the step size is fixed, $E[d^4] = d^4$ and $E[d^2] = d^2$. Using these in Eqn. (5):

$$\frac{3}{8n}\left(\frac{r^4}{2n^2d^4}-\frac{2r^2}{nd^2}+1\right) \leq \epsilon \qquad (6)$$

which can be simplified to

$$3r^4 \leq 16\epsilon n^3 d^4 - 6n^2 d^4 + 12nr^2 d^2. \qquad (7)$$

When n is large, we have $n^3 \gg n^2 \gg n$ and we can approximate the equation above be neglecting the lower order terms. Then we have

$$n \geq \sqrt[3]{\frac{3r^4}{16\epsilon d^4}}. \qquad (8)$$

■

Thus for large enough n the PDF of the distance traveled by the sink is Rayleigh and is given by

$$\text{Prob}\{R(t) \leq r\} = 1 - e^{-\frac{\tau r^2}{td^2}}, \qquad 0 \leq r \leq \infty \qquad (9)$$

Now consider an arbitrary sensor with transmission radius R_t in range of the sink with the location of the sink being equally likely anywhere within the circle describing the sensor's transmission region. Then from the results in [13], the probability β that the sink is still within the range of the sensor after time t is given by

$$\beta = \sum_{k=1}^{\infty} \frac{(a)_k z^k}{(b)_k k!} \qquad (10)$$

where $a = 1/2$, $b = 2$, $z = -4\tau R_t^2/(td^2)$ and $(a)_k$ and $(b)_k$ are Pochhammer symbols: $(a)_k = a(a+1)(a+2)\cdots(a+k-1)$ and $(a)_k = b(b+1)(b+2)\cdots(b+k-1)$. For the desired sink miss rate β after the end of t units of time, Eqn. (10) can then be solved to obtain the required update frequency $1/t$.

C. SSP's Adaptability to Topology Variations

Our scheme adapts to node insertions and deaths fairly easily. When a new sensor joins the network, it can simply start to forward any received swarm agent to let its neighbors be aware of its existence. When a sensor leaves or dies, its upstream neighbors will not receive any further swarm agent, which naturally removes the node from their next hop candidate lists.

V. SIMULATION RESULTS

In this section we use simulations to evaluate the performance of our protocol and also compare SSP with the TTDD algorithm designed for mobile sink scenarios in [3]. SSP outperforms TTDD even when all simulation settings are set to benefit TTDD and a large percentage of the overhead is ignored. We also evaluate the effect of various control and environment factors on SSP's performance.

A. Comparison with TTDD

In this section we compare SSP with TTDD and show that a critical drawback of TTDD is its energy unawareness, which degrades its performance even when we ignore its higher protocol overhead. We consider a network of 100 nodes located in a 100×100 region. The area is divided into 10×10 grids and all nodes are located at cross points of grids. With this arrangement the overhead induced by each source to construct and maintain the grid in TTDD is totally ignored.

The swarm agent is 1 byte and the average data length is 10 bytes. The sink node's movement is assumed to be a 2-dimensional random walk with speed 10m/s with steps of duration 1s. Generation of data reports at each node obeys a Poisson process with rate $\lambda = 0.05$ messages per second. We use the 1st order radio model described in [8] to calculate transmission and reception costs.

Figure 3 shows the lifetime of SSP compared with that of near-ideal TTDD with different grid sizes. Aside from the major drawback of energy unawareness that we mentioned earlier, another issue in TTDD is that each source has to repeatedly construct and maintain its own grid, which spans the whole network and is a major obstacle for TTDD to perform efficiently. It should be noted that the TTDD's overhead actually grows unboundedly with the increase of the number of source nodes and decrease of the grid size, which makes it unscalable.

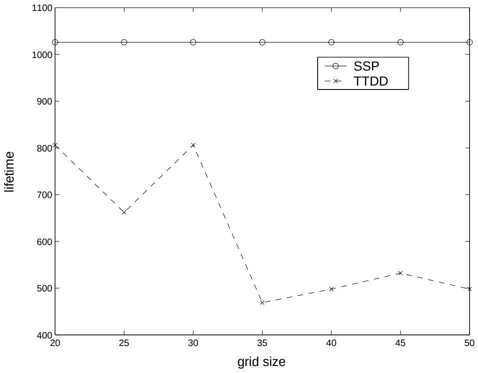

Fig. 3. Lifetime comparison between SSP and TTDD with different grid sizes.

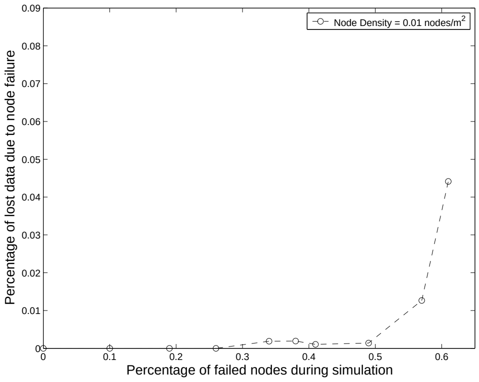

Fig. 5. Effect of node failures on data acquisition.

B. Effect of Control and Environmental Factors

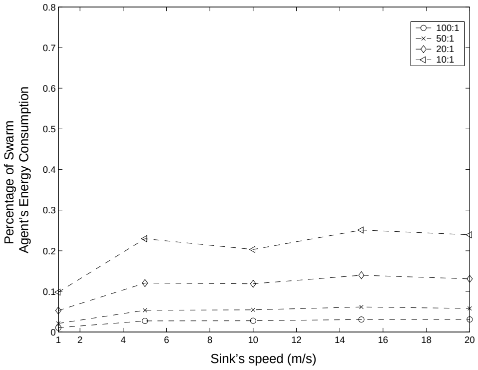

Fig. 4. Effect of Sink's Speed and swarm agent's length relative to the data report's length.

1) Effect of Sink's Speed and Length of the Swarm Agent: Figure 4 shows the effect of the sink's speed and the ratio of data length and swarm agent length on the energy consumption induced by the swarm agent. It can be seen that for different length ratios, energy consumption induced by the swarm agent slightly increases as the sink moves faster. When the swarm agent is much smaller than the data, the energy consumption induced by the swarm agent can be as low as 1%-5%. This suggests that data aggregation at the source area could be employed to decrease SSP's overhead.

2) Effect of Node Failures: In Figure 5 we plot the data acquisition's failure rate as a function of the number of dead nodes. The node density is 0.01 nodes per m^2 and data generation at each node is Poisson with $\lambda = 0.05$. To generate the death events, nodes were picked randomly and at random times. The simulation shows that SSP is very robust in that its data acquisition failure rate stays below 5% even when more than half of the nodes fail to function.

VI. CONCLUSIONS

This paper presents an energy aware surveillance protocol using sensor networks with mobile sinks: SSP. It is designed based on techniques of swarm intelligence and energy-wise path definition for dynamically updating the shortest paths. The swarm intelligence approach maximizes individual node's lifetime since it greatly simplifies sensor's operations, keeping requirements in line with a typical sensor's low computational capabilities, restricted storage and limited energy. The protocol tries to maximize the network's lifetime by dynamically choosing the energy efficient paths and balancing the residual energy at each node. We analytically verify the validity of SSP. Extensive simulations are also reported to demonstrate its robustness and superior performance as compared to the existing protocol.

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