

Mobile Sensor Networks Self-organization for System Utility Maximization: Work in Progress

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Abstract— This paper reports on work in progress on mobile sensor network self-organization for system utility maximization with system utility being the difference between the aggregate utility of sensor information and penalty associated with sensor battery energy expenditure. We assume that location-dependent marginal utility of each sensor is determined and communicated back to the corresponding sensor by the sensor information access point, where the information streams from all sensors are fused into coherent picture. Self-organization takes place in two time scales: in the fast time scale sensors form and optimize multi-hop Mobile Ad-hoc Network (MANET) with sensors cooperating by relaying other sensor information possibly in addition to transmitting their own information. Optimized in the fast time scale system utility determines potential fields and virtual forces guiding sensor repositioning in the slow time scale.

Keywords—mobile sensor network, self-organization, utility, lifespan, potential field.

I. INTRODUCTION

Mobile sensor networks are envisioned for detecting and tracking potential targets and events for civilian as well as military purposes. Locations of sensors in a mobile sensor networks affect both their ability to acquire information on the intended targets and events as well as their ability to communicate this information to the intended recipients. The information acquisition needs, which require proximity to the target(s), often compete with communication needs, which require proximity to the recipient of sensor information. The communication ability can be improved if sensors are capable of forming and optimizing a multi-hop Mobile Ad-hoc Network (MANET) with some sensors relaying the other sensor information possibly in addition to transmitting their own information.

The network Utility Maximization (NUM) framework for cross-layer network optimization has been successfully applied in various networking domains from wire-line network to MANET [1]-[3]. NUM optimizes trade-offs between demands of different users in a networked system by a distributed, price-based algorithm. We propose NUM extension to mobile sensor networks intended to balance competing mobile sensor network information acquisition and communication goals. Since achieving both these goals depends on the sensor locations relatively to the target(s), to the access point, and to each other, the system utility to be maximized is a complex function of sensor rates and locations.

The appeal of this unified view of mobile sensor network optimization is that while system utility maximization over sensor information flow rates in “fast” time scale yields the optimal cross-layer design of the sensor MANET, system utility maximization over sensor locations in “slow” time scale guides sensor repositioning [4].

However, realization of this vision requires ability to quantify the sensor rate and location dependent system utility. Due to possible redundancy of information acquired by different sensors, the aggregate utility of sensor information streams may not be the sum of utilities of information streams from different sensors. It is natural to assume that the sensor information recipient, who fuses all sensor information into coherent picture, is in the position to estimate the marginal utility of each sensor information stream. On the other hand, each mobile sensor has direct knowledge of its remaining battery power supply and surrounding terrain which affect sensor ability to communicate and relocate. We resolve this information asymmetry by assuming that mobile sensor network self-organization is “guided” by the sensor information access point.

Given sensor $s \in \mathcal{S}$ locations $x = (x_s)$, the sensor information access point (destination) D quantifies and communicates to each sensor s the marginal value of this sensor information $w_s(x) \geq 0$. Each sensor s combines “global” information $w_s(x)$ with locally available information, which may include remaining battery power supply, local terrain and conditions of neighboring sensors, to decide on the transmission rate, routing, relaying other sensor streams, and repositioning. This scheme naturally leads to a proportionally-fair NUM framework for sensor MANET cross-layer optimization with parameters $w_s(x)$ playing role of access point D “willingness-to-pay” for sensors $s \in \mathcal{S}$ information streams [1]. Optimized in the “fast” time scale system utility determines the local potential field and the corresponding virtual forces guiding sensor repositioning in the “slow” time scale. The paper is organized as follows. Section II describes the self-organization framework. Section III demonstrates feasibility of this framework in a practically important case of power-limited sensor network. Finally, the conclusion summarizes the proposed approach and outlines future research directions.

II. SELF-ORGANIZATION FRAMEWORK

Consider mobile sensor network where each sensor $s \in \mathcal{S}$ maintains two-way communications with a single access (destination) point D . The sensor communications include delivering sensor information to D and receiving control information from D . We assume that the overall mobile sensor network performance can be quantified by system utility (social welfare)

$$W = U - V \quad (1)$$

In (1) the aggregate utility of sensor information streams U is some unknown in advance function of sensor $s \in \mathcal{S}$ information rates $\lambda = (\lambda_s)$ and locations $x = (x_s)$: $U = U(\lambda, x)$, while penalty V is associated with draining sensor battery power supply for sensor transmissions and motion.

From algorithmic perspective mobile sensor network self-organization requires resolving three major issues: (a) specifying the overall system performance criterion (1), (b) identifying the individual mobile sensor utilities, and (c) developing mobile sensor adaptation to maximize their individual utilities so that these individual optimizations result in the system utility (1) maximization. The rest of this paper attempts to prove the concept of mobile sensor network self-organization based on the following key idea. Since all sensor information flows are fused at the access point D , which has the greatest computational capability in the system, we assume that D estimates partial derivatives

$$w_s(x) \stackrel{\text{def}}{=} \lambda_s \frac{\partial U(\lambda, x)}{\partial \lambda_s} \quad (2)$$

and propagates values (2) to the corresponding mobile sensors $s \in \mathcal{S}$.

Once parameters (2) are known, the aggregate utility of sensor information streams can be estimated as follows:

$$U = \sum_{s \in \mathcal{S}} w_s(x) \log \lambda_s \quad (3)$$

and the goal of self-organization can be defined as maximization of the following system utility:

$$W = \sum_{s \in \mathcal{S}} w_s(x) \log \lambda_s - V \quad (4)$$

Given mobile sensor locations $x = (x_s)$, system utility (4) maximization results in proportionally-fair allocation of sensor MANET resources with parameters $w_s(x)$ representing system “willingness-to-pay” for sensor $s \in \mathcal{S}$ information stream of rate λ_s [1].

We assume the aggregate penalty in (1) to be the sum

$$V = \sum_{s \in \mathcal{S}} v_s(p_s) \quad (5)$$

of penalties $v_s(p_s)$ quantifying effect of draining sensor s battery power supply at rate p_s . Transmission power cost

$v_s(p)$ is time t dependent through the target transmission power $\tilde{p}_s(t) = E_s(t)/\tau_s(t)$:

$$v_s(p) = \psi_s(p/\tilde{p}_s) \quad (6)$$

where the remaining battery energy level is $E_s(t)$ and target node future life expectancy is $\tau_s(t)$ [5]. Penalty functions $\psi_s(z)$ in (6) are monotonously increasing and convex in $z \geq 0$, and selected to be flat for $z \ll 1$ and steeply increasing as z approaches one. A convenient two-parameter approximation for function $\psi_s(z)$ is

$$\psi_s(z) = A_s z^{a_s} \quad (7)$$

where $A_s > 0$ and $a_s > 1$ are some parameters. Here we only consider sensor battery energy expenditure on communication:

$$p_s = \sum_j p_{sj} \quad (8)$$

when sensor $s \in \mathcal{S}$ transmission power to another sensor $j \in \mathcal{S} \setminus s$ or destination $j = D$ is p_{ij} . An approach to accounting for sensor battery energy expenditure for sensor repositioning has been proposed in [4].

We consider interference-limited sensor MANET without multi-user detection when link (i, j) capacity c_{ij} is an increasing function of the Signal-to-Interference Ratio on this link:

$$SIR_{ij} \stackrel{\text{def}}{=} \frac{p_{ij} \xi(x_i, x_j)}{\omega(x_j) + \sum_{(n,k) \neq (i,j), n \in \mathcal{S} \setminus i} p_{nk} \xi(x_n, x_j)} \quad (9)$$

where $\xi(x_i, x_j)$ is the path loss from sensor $i \in \mathcal{S}$ located at point x_i , to another sensor $j \in \mathcal{S} \setminus s$ or destination $j = D$ located at point x_j , and $\omega(x_j)$ is the noise power at the receiver.

Given sensor $s \in \mathcal{S}$ locations $x = (x_s)$ and rates $\lambda = (\lambda_s)$, NUM determines optimal power control and packet scheduling in “fast” time scale by minimizing penalty associated with draining battery power supply

$$V^*(\lambda, x) = \min_p \sum_{s \in \mathcal{S}} v_s \left(\sum_j p_{sj} \right) \quad (10)$$

subject to the wireless link ability to sustain given vector of information flows λ . Recent results [3] suggest that solution to inherently centralized optimization problem (10) can be approximated by a decentralized algorithm at the cost of small increase in penalty (10).

Given sensor $s \in \mathcal{S}$ locations $x = (x_s)$, NUM determines optimal flow control and routing in “slower” time scale by maximizing the system utility:

$$W^*(x) = \max_{\lambda} \left(\sum_{s \in S} w_s(x) \log \lambda_s - V^*(\lambda, x) \right) \quad (11)$$

subject to the corresponding link capacity constraints. Depending on the optimization variables and constraints, either link-centric or node-centric optimization schemes (11) are possible. Here we only note that both schemes can be implemented by distributed, price-based algorithms.

Sensor repositioning, occurring on the “slowest” time scale is aimed at maximizing system utility (11) over sensor locations $x = (x_s, s \in S)$:

$$x^* = \arg \max_{x \in X} W^*(x) \quad (12)$$

where X is the corresponding feasible region for sensor locations.

Sensor location dependent system utility (11) defines potential field $H(x) = -W^*(x)$ and the corresponding virtual forces

$$F_s(x) = \nabla_{x_s} W^*(x) \quad (13)$$

driving sensors $s \in S$ towards locally optimal location, for example, following trajectories of potential dynamic system

$$\dot{x}_s = F_s(x) \quad (14)$$

where $\nabla_{x_s} = (\partial/\partial x_{s1}, \partial/\partial x_{s2})$ is gradient vector, and $x_{si}, i=1,2$ are components of two-dimensional vector $x_s = (x_{s1}, x_{s2})$ [6].

III. POWER-LIMITED SENSOR NETWORK

This section demonstrates feasibility of the described in the previous section self-organization framework in a practically important case of power-limited sensor network. In this case interference created by simultaneous transmissions by different sensors is negligible as compared to the noise at the receivers:

$$\sum_{(n,k) \neq (i,j), n \neq i, j} p_{nk} \xi(x_n, x_j) \ll \omega(x_j), \quad (15)$$

and thus Signal-to-Interference Ratio on a link (i, j) is a function of the transmission power on this link only:

$$SIR_{ij} \approx p_{ij} \xi(x_i, x_j) / \omega(x_j) \quad (16)$$

In this case, given sensor locations $x = (x_s)$, the sensor MANET can be optimized and sensor location dependent utility (11) can be evaluated efficiently and sometimes explicitly as functions of the system willingness-to-pay for the sensor information streams, sensor remaining power supply and path gains on the wireless links.

For simplicity we consider a symmetric, threshold-based wireless channel model where $\xi(x_i, x_j) = \xi(x_j, x_i)$, and wireless link $l = (i, j)$ of fixed capacity $c_{ij} > 0$ exists if and only if Signal-to-Interference Ratio on this link exceeds certain threshold $\chi_{ij} > 0$:

$$c_{ij}(p) = \begin{cases} c_{ij} & \text{if } SIR_{ij} \geq \chi_{ij} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

Consider network optimization (10)-(11) subject to each mobile sensor $s \in S$ maintaining two-way communication with the access point D at some minimally acceptable rate λ_{\min} , given sensor locations $x = (x_s)$. This optimization yields the sensor network undirected graph $G = (N, L)$ with set of nodes $N = S \cup D$ and set of links L where each sensor $s \in S$ is connected with the access point D . The power control optimization control problem (10) can be solved explicitly:

$$V_*(\lambda, x, L) = \sum_{s \in S} v_s \left(\sum_{j: (s,j) \in L} p_{sj}^*(x_i, x_j) \right) \quad (18)$$

where the minimum transmission power on a link (i, j) is

$$p_{ij}^*(x_i, x_j) = \chi_{ij} \omega(x_j) / \xi(x_i, x_j) \quad (19)$$

The optimal topology $L = L^*(x)$ is determined by optimization problem (11)

$$W^*(x) = \max_L \left(\log(\lambda_{\min}) \sum_{s \in S} w_s(x) - V_*(\lambda, x, L) \right) \quad (20)$$

Here without elaboration we only note that the optimization problem (20) can be solved and optimal sensor network topology $L = L^*(x)$ can be efficiently determined by a distributed algorithm.

Virtual forces (13) generated by utility (20) include two components:

$$F_s(x) = F_s^{(1)}(x) + F_s^{(2)}(x) \quad (21)$$

The first component is virtual force pushing sensor s in the direction of higher value of the aggregate sensor information stream:

$$F_s^{(1)}(x) = \log(\lambda_{\min}) \nabla_{x_s} \sum_{s \in S} w_s(x) \quad (22)$$

The second component is virtual force pushing sensor s in the direction of prolonging sensor network life expectancy by reducing battery energy consumption:

$$F_s^{(2)}(x) = \sum_{i: (s,i) \in L} f_{si}(x_s, x_i) + \sum_{i: (i,s) \in L} f_{is}(x_i, x_s) \quad (23)$$

where

$$f_{ij}(x, p_i) = -v'(p_i) \chi_{ij} \nabla_{x_s} [\omega(x_j) / \xi(x_i, x_j)] \quad (24)$$

Virtual forces (21)-(24) are not known in advance and should be estimated as mobile sensors relocate. This dual purpose sensor mobility for learning and increasing the system utility is similar to evolutionary adaptation to unknown fitness landscape. Typical multiplicity of local minima of the aggregate loss, which creates a possibility of sensor trapping, further complicates decentralized sensor relocation [6].

We are planning to explore using evolutionary algorithms for sensor repositioning. The first step in this exploration is

identifying local potential to be minimized by each mobile sensor so that this individual optimization results in the system utility maximization. The rest of this section briefly demonstrates that it can be done in a case of a mobile sensor network tracking a single target T . Under some natural assumptions it can be shown that in this case optimization problem (20) yields linear network topology with only one sensor $s = S$ acquiring target information and the rest of the sensors $s = 1, \dots, S-1$ serving as relays. It is convenient to define Cartesian coordinates $x = (x_1, x_2)$ in such way that the access point D is located at the origin: $x_D = (0, 0)$ and the abscissa axis is directed from D to the target T : $x_T = (x_{1T}, 0)$. In this linear topology network information flows from the target to the destination as follows: $D \leftarrow (s=1) \leftarrow \dots \leftarrow (s=S) \leftarrow T$, while the control information flows in the opposite direction: $D \rightarrow (s=1) \rightarrow \dots \rightarrow (s=S)$, where we ordered sensors to simplify notations. Utility (20) associated with this topology is

$$W^*(x) = \log(\lambda_{\min})w(x_s|x_T) - V(x) \quad (25)$$

In (25) willingness-to-pay $w(x_s|x_T)$ for target T information acquired by sensor $s = S$ depends on the sensor and target positions x_s and x_T respectively. The aggregate penalty associated with draining sensor battery energy is

$$V(x) = \varphi_s \left[\frac{\chi \omega(x_{s-1})}{\xi(x_s, x_{s-1})} \right] + \sum_{s=1}^{s-1} \varphi_i \left\{ \chi \left[\frac{\omega(x_{i-1})}{\xi(x_i, x_{i-1})} + \frac{\omega(x_{i+1})}{\xi(x_i, x_{i+1})} \right] \right\} \quad (26)$$

where for simplicity we assumed $\chi_{s,s-1} = \chi_{s,s+1} = \chi$.

Maximization of its own utility by each sensor may result in very poor overall system performance. For example, each sensor $s = 1, \dots, S-1$ attempting to minimize its battery energy draining penalty while maintaining communication with neighboring sensors $s-1$ and $s+1$ has incentive to position itself at point x_s , where $\xi(x_s, x_{s-1}) = \xi(x_s, x_{s+1})$, without any consideration for possible difference in sensor $s-1$ and $s+1$ remaining battery energy levels. In a case of linear topology it is easy to identify sensor "local potentials" V_s so that minimization V_s by each sensor $s = 1, \dots, S$ maximizes the overall system performance. In particular, sensors $s = 1, \dots, S-1$ local potentials are

$$V_s(x_s, x_{s-1}, x_{s+1}) = \varphi'_s(p_s) \left[\frac{\omega(x_{s-1})}{\xi(x_s, x_{i-1})} + \frac{\omega(x_{i+1})}{\xi(x_i, x_{i+1})} \right] + \varphi'_{s-1}(p_{s-1}) \frac{\omega(x_s)}{\xi(x_{s-1}, x_s)} + \varphi'_{s+1}(p_{s+1}) \frac{\omega(x_s)}{\xi(x_{s+1}, x_s)} \quad (27)$$

where $x_0 = x_D$. We intend to extend these results to a general topology sensor network.

IV. CONCLUSION AND FUTURE RESEARCH

This paper has proposed a framework for self-organization of mobile sensor networks, which includes cross-layer network optimization as well as controlled sensor mobility. Given sensor locations, cross-layer network optimization allocates resources and configures protocols to ensure the delivery of the highest utility of the sensor information to the access point taking into account battery energy conservation needs. The proposed framework allows one to overcome deficiencies of numerous existing phenomenological approaches to sensor mobility control [6]. In these approaches potential fields and corresponding virtual forces are defined phenomenologically without accounting for the specific sensor information acquisition and communication needs, e.g., different "power costs" of mobile sensors with different remaining battery energy levels.

We are planning to concentrate our future efforts on two major issues in sensor mobility control. The first issue is quantification of the battery energy required for sensor mobility. This quantification can be made locally, based on the surrounding terrain [4]. The second issue is estimation of the sensor local potential guiding sensor motions. Since sensors acquiring target information do not know in advance their local potentials, we expect that biologically inspired algorithms may be the best approach to combining sensor adaptation to the unknown "fitness landscape" with exploratory moves [7].

V. ACKNOWLEDGEMENTS

Authors acknowledge the support of the NIST "Pervasive Computing" initiative.

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