A Framework for Joint Cross-Layer and Node Location Optimization in Mobile Sensor Networks

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Abstract. This paper proposes an extension to Network Utility Maximization (NUM) framework, referred to as L-NUM (Location-aware NUM). This framework is intended to characterize both the amount of the received sensor information and the network ability to deliver the information to the intended recipient(s). The sensor location is controlled by maximization of the system utility production, which accounts for both rate of the network utility increase and the negative effects of the energy consumption as a result of sensor motion. Definition of sensor utility in L-NUM incorporates the value of sensor information which is affected by sensor locations. Once model-specific network utility and system utility production are defined, L-NUM provides intuitively appealing and tractable framework for mobile sensor network optimization.

1 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 the network ability to detect and track the identified targets and events as well as the ability to communicate the relevant information to the intended recipients. The communication ability can be improved if sensors are capable of optimally self-organizing into a multihop mobile network where sensors cooperate in relaying each other information in addition to transmitting their own information. Since the detecting and tracking needs could potentially compete with the communication needs, optimal realization of mobile sensor networks requires node ability to balance these competing requirements using local, and typically incomplete, information. Energy conservation requirements could also be a major factor in controlling sensor position due to their possible impact on the sensor lifespan and in turn on the rest of the network performance. Developing self-organized mobile sensor networks capable of adjusting to target movement and/or other environmental changes requires developing sophisticated algorithms capable of balancing numerous inherent trade-offs. This paper proposes a tractable extension to Network Utility Maximization (NUM) framework aimed at addressing some of these algorithmic challenges.

NUM framework for fair bandwidth allocation in a wire-line network has been proposed in [1]. This framework assumes elastic users, sources or applications whose satisfaction can be quantified by a utility function of the corresponding end-to-end bandwidth. Framework [1] assumed that elastic users/sources are capable of adjusting their bandwidth requirements in response to the network congestion. This framework has been extended to include cross-layer optimization of wire-line as well as wireless networks [2]-[4]. The extended NUM jointly optimizes flow control, routing, scheduling and power control. The optimization is achieved by a decentralized, adaptive closed-loop algorithm with feedback signals which can be interpreted as resource congestion prices.

In [5], a combination of utility-based flow model with potential field based approach to control the sensor positions has been proposed. This hybrid framework accounts for the effect of sensor locations on their ability to transmit sensor information to the intended recipient(s). This is achieved through link capacity constraints in the mobile ad-hoc network formed by the sensors. The corresponding optimal, location-dependent network utility, viewed as a potential field, defines potential forces guiding the sensors motion. However, the network utility only quantifies communication abilities of the sensor network and does not take into account the effect of sensors locations on the sensor ability to get valuable information on the target(s). Instead, the value of sensor information is incorporated through phenomenologically defined forces, e.g., “attractive forces towards goals”. Also, sensor motion in [5] is guided by a mass-damper model driven by the sum of the potential and phenomenological forces with damping coefficients that represent the energy expended on the sensor motion.

Here, we propose another utility-based framework for mobile sensor network optimization, referred to as Location-aware Network Utility Maximization (L-NUM). L-NUM assumes that the aggregate sensor utility quantifies the value of the sensor information, which is a function of both sensor information rates and sensor physical locations. Given sensor locations, aggregate sensor utility maximization subject to the communication constraints yields the optimal cross-layer network design. The corresponding optimal sensor network utility quantifies both value of sensor information and ability of the network to deliver this information to the intended recipient(s). The maximum of this aggregate network utility yields the optimal sensor locations. In practice, reaching these optimal locations by mobile sensors may be infeasible due to the un-accessible terrain and/or limitations on the node energy supply. L-NUM proposes to account for these factors through utility production, which is a function of both, sensors locations and speeds. The sensor speeds are selected to maximize the utility production, given the sensor locations.

Once the model-specific network utility and system utility production are defined, L-NUM provides intuitively appealing, self-contained and tractable framework for mobile sensor network optimization. This paper describes L-NUM framework with a very brief discussion of some of the numerous methodological, computational and implementation issues. The main methodological issues include quantifying the location-dependent value of sensor information, i.e., sensor utility, as well as utility production. Computational and implementation issues include decentralized optimization based on local and typically incomplete information.

The rest of this paper is organized as follows. Section II summarizes the conventional NUM framework. Section III describes L-NUM as a natural extension of the conventional NUM by incorporating spatial effects into cross-layer optimization and energy conservation considerations into position control. Section IV briefly illustrates L-NUM on an example of single mobile sensor transmitting information to a single receiver. Finally, Conclusion summarizes the proposed approach and outlines direction for future research.

2 Network Utility Maximization

Consider a network comprised of a set of sources S and a set of resources (i.e. links) $l \in L$ with capacities c_l. Each source $s \in S$ identifies a unique source-destination pair and a set of feasible routes R_s. Each route $r \in R_s$ is a collection of resources $l \in r$. Source s satisfaction of having end-to-end bandwidth λ is characterized by the utility function $u_s(\lambda),\ s \in S$ which is assumed to be monotonically increasing and concave in $\lambda \geq 0$. For example, widely used weighted (α, w) - fair rate allocation [6] is based on utilities

$$u_s(\lambda) = \begin{cases} w_s \dfrac{\lambda^{1-\alpha}}{1-\alpha} & if \quad \alpha \neq 1 \\ w_s \ln \lambda & if \quad \alpha = 1 \end{cases}, \tag{1}$$

where $\alpha, w_s > 0$ are parameters. When $w_s = 1$, the cases $\alpha \to 0$, $\alpha \to 1$ and $\alpha \to \infty$ correspond respectively to an allocation which achieves maximum throughput, and is proportionally fair or max-min fair.

In a link-centric formulation each source $s \in S$ with end-to-end rate λ_s is split into rates λ_r over feasible routes $r \in R_s$:

$$\lambda_s = \sum_{r \in R_s} \lambda_r \tag{2}$$

This results in the aggregate load μ_l on link $l \in L$ where

$$\mu_l = \sum_s \sum_{r: l \in r \subseteq R_s} \lambda_r \tag{3}$$

The link-centric utility maximization framework selects vector of flow rates $\Lambda = (\lambda_r, r \in R_s, s = 1,.., S)$ which maximizes the aggregate user utility

$$U_\Sigma(\lambda) = \sum_s u_s(\lambda_s)\,. \tag{4}$$

where $\lambda = (\lambda_s, s = 1,.., S)$. This maximization is subject to the link capacity constraints $\mu_l \leq c_l$, (2) and (3).

One can also account for capacity constraints $\mu_l \leq c_l$ through congestion penalty

$$F_{\Sigma}(\mu,c)=\sum_l f_s(\mu_l,c_l)\,, \tag{5}$$

where $\mu=(\mu_l, l\in L)$, $c=(c_l, l\in L)$. Penalty function $f_l(\mu_l,c_l)$ quantifies losses in terms of delays or packet loss due to buffer overflows as the link l utilization μ_l approaches link capacity c_l. Functions $f_l(\mu_l,c_l)$ are assumed to be monotonically increasing and convex in $\mu_l>0$. A steep function $f_l(\mu_l,c_l)$ increase as μ_l approaches c_l prevents violation of the capacity constraints. NUM with capacity constraints incorporated through the congestion penalty can be expressed as follows

$$U^*=\max_{\Lambda\geq 0}\{U_{\Sigma}(\lambda)-F_{\Sigma}(\mu,c)\} \tag{6}$$

where maximization is subject to constraints (2) and (3). Such formulization and its distributed price-based solution have been proposed in [1].

While in a wire-line network link capacities c_l are typically assumed fixed, in a wireless, interference-limited network link capacities are functions of the transmission powers on neighboring links and channel conditions affecting transmission on link l as well as interference from transmissions on other links. A large number of cross-layer optimization frameworks accounting for these interactions have been proposed, e.g., see [2]-[4]. These frameworks often assume that "elastic" link capacities are given functions of the vector of average transmission powers on all links ($p=(p_l, l\in L)$) i.e.:

$$c_l=c_l(p) \tag{7}$$

For example, [4] assumes

$$c_l(p)=k_1\log[1+k_2 SIR_l(p)]\,, \tag{8}$$

where k_1, k_2 are constant coefficients, and the Signal-to-Interference Ratio on link $l=(i,j)$ is

$$SIR_{ij}=\frac{p_{ij}\xi_{ij}}{\eta_j+\sum_{(n,k)\neq(i,j),n\neq i,j}p_{nk}\xi_{nj}} \tag{9}$$

In (9) ξ_{ij} is the path loss on link (i,j), and η_j is the noise power at the receiver of node j.

Elasticity of the link capacities in a wireless network naturally lead to the following NUM formulation:

$$U^*=\max_{\Lambda\geq 0}\{U_{\Sigma}(\lambda)-F_{\Sigma}(\mu,c)\} \tag{10}$$

with maximization to be subject to capacity constraints (2)-(3), wireless channel model (7), and possibly power constraints

$$p\in P \tag{11}$$

where P is the feasible power region. Much more sophisticated versions of NUM could also include optimization over packet scheduling on different links [2]-[4].

3 Location-aware NUM

Joint Cross-Layer and Node Location Framework Model

Here, we propose a location-aware extension of NUM for mobile sensor networks by assuming that the aggregate value of the information gathered by S sensors can be quantified by the utility function $U_\Sigma(\lambda, x)$, where vectors $\lambda = (\lambda_1,..,\lambda_S)$, $x = (x_1,..,x_S)$ describe information collection rates λ_s and physical locations (coordinates) x_s of all sensors $s = 1,..,S$.

We assume that the aggregate utility $U_\Sigma(\lambda, x)$ is additive:

$$U_\Sigma(\lambda, x) = \sum_s U_s(\lambda_s, x) \tag{12}$$

where utility (i.e. information value) of each sensor $s = 1,..,S$ information is the following product

$$U_s(\lambda_s, x) = u_s(\lambda_s) v_s(x) . \tag{13}$$

The first multiplier $u_s(\lambda_s)$ is an increasing and concave function of the information collection rate λ_s, e.g., of form (1). The second multiplier $v_s(x)$ quantifies the effects of the physical locations of all S sensors $x = (x_1,..,x_S)$ on the value of information captured by the sensor s. The dependence of $v_s(x)$ on the physical locations of all S sensors $x = (x_1,..,x_S)$ can be explained as follows. While the value of the information collected by a single sensor s from the intended target(s) depends on the sensor physical location x_s relative to the target(s), this value can be reduced if other sensors are located close to sensor s due to redundancy of the obtained information. In a situation when all S sensors $s = 1,..,S$ gather information from a single target, it is natural to assume that utilities $v_s(x)$ depend on the target location x_T: $v_s(x) = v_s(x|x_T)$

Physical location of mobile sensors $x = (x_1,..,x_S)$ also affects the quality of wireless channels between different sensors and between sensors and the intended recipient(s) of the sensor information. This is modeled by considering that capacity c_{ij} of the wireless link l=(i, j) depends on the locations of sensors i, j (i.e. x_i, x_j):

$$c_{ij} = c_{ij}(p_{ij}, x_i, x_j) \tag{14}$$

In particular, the path loss component in (9) is a function of the locations of the two communicating sensors i.e.

$$\xi_{ij} = \xi_{ij}(x_i, x_j) \tag{15}$$

For example, in case of free-space propagation [7]:

$$\xi_{ij} = \chi_{ij} \rho_{ij}^{-\gamma} \tag{16}$$

where χ_{ij} and γ are positive constants, and $\rho_{ij} = \rho(x_i, x_j)$ is the physical distance between sensors i and j with physical coordinates x_i and x_j respectively.

As a result of these spatial effects, the optimal network utility (10) is a function of the vector of sensor locations $x = (x_1,..,x_S)$

$$U^*(x) = \max_{\Lambda, P \geq 0} \{U_\Sigma(\lambda, x) - F_\Sigma[\mu, c(p, x)]\} \tag{17}$$

where the maximization is subject to capacity constraints (2)-(3) and power constraints (11). For the case of a single target and destination, optimal utility (17) depends on the target and destination locations x_T and x_D respectively, i.e. $U^*(x) = U^*(x | x_T, x_D)$.

Location Optimization

For given sensor locations $x = (x_1,..,x_S)$, the cross-layer optimized utility can be obtained by solving equation 17. The optimal sensor locations $x^{opt} = (x_1^{opt},..,x_S^{opt})$ maximize this cross-layer optimal utility by:

$$x^{opt} = \arg\max_{x_s \in A_s} U^*(x) \tag{18}$$

where A_s is the allowable (or feasible) area for sensor s. Terrain information including unreachable or undesirable locations can be incorporated here.

Sensor motion (i.e. trajectory) should also take into account the corresponding energy consumption. To account for the "cost" of sensor s motion, we introduce a dissipative function $\varphi_s(x_s, \dot{x}_s)$ which quantifies negative effect of energy supply depletion as a result of sensor s motion with speed $\dot{x}_s$ at location x_s. Functions $\varphi_s(x_s, \dot{x}_s)$ are assumed to be monotonically increasing and convex in $\dot{x}_s$. Also, $\varphi_s(x, \dot{x}_s) > 0$ if $\dot{x}_s \neq 0$ and $\varphi_s(x_s, \dot{x}_s) = 0$ if $\dot{x}_s = 0$.

We assume that the total "cost" of sensor motion is additive:

$$\Phi(x, \dot{x}) = \sum_s \varphi_s(x_s, \dot{x}_s) \tag{19}$$

where $\dot{x} = (\dot{x}_1,..,\dot{x}_S)$ is the vector of sensors velocities. Now consider the effect of sensor s motion on the system performance. The rate of network utility change due to the sensor motion is

$$\dot{U} = \dot{x} \nabla_x U^*(x) = \dot{x} \left(\sum_s \nabla_x U_s^*(x) - \sum_l \nabla_x f_l^* \right) \tag{20}$$

where $\nabla_x = (\partial/\partial x_1,..,\partial/\partial x_n)^T$. Functions $U_s^*(x) = U_s[\lambda^*(x), x]$ and $f_l^*(x) = f_s[\mu^*(x), x]$ in (2) are calculated at the optimum (17). Expression (20) implies that cross-layer optimization (17) is performed at much faster time scale than sensors change their locations.

Now, define system utility production $W(x,\dot{x})$ as

$$W(x,\dot{x}) = \dot{U}(x) - \Phi(x,\dot{x}) \quad (21)$$

where network utility production $\dot{U}$ is given by (20) and dissipative function $\Phi(x,\dot{x})$ is given by (19). We propose to control sensor position by selecting sensor velocity vector $\dot{x}$, which maximizes the utility production (21):

$$\dot{x} = \arg\max_{\dot{x}} W(x,\dot{x}) \quad (22)$$

Interpreting (22) as a dynamic system, one can realize that since $\Phi(x,\dot{x})\big|_{\dot{x}=0} \equiv 0$, the optimal sensor location x^{opt} is an equilibrium point of this dynamic system. It is clear from (21)-(22) that the optimal sensor motion depends on both, potential $U(x)$ and the nature of the friction affecting the dissipative function $\Phi(x,\dot{x})$. For brevity, we only consider two particular cases of static and viscous friction. We assume that $x_s = (x_{sm})$ are Cartesian coordinates of sensor s with components x_{sm}.

In the case of static friction, sensor s dissipative function is

$$\varphi_s(x,\dot{x}_s) = \sum_m a_{sm}(x)\left|\dot{x}_{sm}\right| \quad (23)$$

and in the case of viscous friction, sensor s dissipative function is

$$\varphi_{sm}(x,\dot{x}_{sm}) = (1/2)a_{sm}(x_s)(\dot{x}_{sm})^2 \quad (24)$$

where positive functions $a_{sm}(x) > 0$ characterizes the "difficulty" of moving sensor s at the direction of the dimension m at the point $x_s = (x_{sm})$. It is easy to see that for static friction (23), sensor s either holds its position x_s if the static friction is sufficiently strong or moves at the highest allowable speed otherwise.

In the case of viscous friction (24), the dynamic system (22) takes the following form:

$$\dot{x}_{sm} = \frac{1}{a_{sm}(x_s)} \nabla_{x_{sm}} \left(\sum_s U_s^*(x) - \sum_l f_l^*(x)\right) \quad (25)$$

Sensor motion (25) balances change in the value of sensor information, represented by the term $\nabla_{x_{sm}} \sum_s U_s^*(x)$, with the change in the sensor ability to deliver this information to the intended recipient, represented by $\nabla_{x_{sm}} \sum_l f_l^*(x)$. Increase in the friction force represented by friction coefficient $a_{sm}(x)$ causes sensor to slow down. In practical situations one may expect a combination of static and viscous friction effects.

4 Example: A Single Mobile Sensor

Consider a single mobile sensor collecting information from a single target and transmitting this information to a single destination. In this case the network utility takes the following form:

$$U(\lambda, p, x) = u(\lambda)v(x) - f[\lambda, c(p, x)] \tag{26}$$

We assume that power constraints (18) impose upper bound on the average transmission power p. It is easy to see that under natural assumptions utility is maximized for the maximum allowable power p. Therefore, power p can be assumed to be fixed in (26). Formal differentiation of the joint utility function (26) with respect to λ yields the following first-order cross-layer optimality conditions:

$$v(x)u'_\lambda(\lambda) = f'_\lambda(\lambda, c) \tag{27}$$

We consider weighted (α, w) fair rate allocation utility (1) for which

$$u'(\lambda) = w\lambda^{-\alpha}; \tag{28}$$

We also consider the following penalty function associated with the communication capacity constraints:

$$f(\lambda) = \frac{\theta^{-1}}{c - \lambda} \tag{29}$$

Parameter θ represents the maximum tolerable communication delay. Equation (29) naturally arises from expression $1/(c-\lambda)$ for the average delay in $M/M/1$ queuing system [8]. Combining equations (27)-(29), we obtain the following first-order cross-layer optimality conditions:

$$\lambda^\alpha / [c(x, p) - \lambda]^2 = w\theta v(x) \tag{30}$$

Equation (30) has a single solution

$$\lambda = \lambda^*(x, p) \tag{31}$$

which is a function of both, sensor location x and transmission power p. Since sensor utility $U(\lambda, x)$ is an increasing function of λ, the optimal sensor location

$$x^{opt}(p) = \arg\max_{x \in A} \lambda^*(x, p) \tag{32}$$

which maximizes sensor information rate also maximizes the utility. In (32), A is the feasible region for the mobile sensors. The optimal sensor motion is characterized by the equation (22).

In some cases, function (32) can be explicitly identified. For example, in the case of $\alpha=0$:

$$\lambda = c(x,p) - [w\theta v(x)]^{-1/2} \tag{33}$$

and, in the case of $\alpha=2$:

$$\lambda = \frac{\sqrt{w\theta v(x)}}{1+\sqrt{w\theta v(x)}} c(x,p) \tag{34}$$

Now, consider the situation of low power transmissions: $p \to 0$, when

$$c(x,p) = c_0(x)p + o(p) \quad as \quad p \to 0 \tag{35}$$

where $c_0(x) > 0$. For example, with the channel capacity expressions in (8)-(9):

$$c_0(x) = k\,\xi(x, x_D)/\eta\,, \tag{36}$$

where k is a constant coefficient, $\xi(x, x_D)$ is the path loss from the sensor location x to the destination location x_D, and η is the noise power at the destination location x_D. We also assume that the sensor tracks a single target with location x_T, and the spatial component of sensor information value depends on both, sensor and target locations: $v(x) = v(x, x_T)$. Under these assumptions equations (33) and (34) take the following forms respectively:

$$\lambda = (k/\eta)\,p\xi(x, x_D) - [\theta w v(x, x_T)]^{-1/2} \tag{37}$$

$$\lambda = (k/\eta)\,p\xi(x, x_D)\frac{\sqrt{\theta w v(x, x_T)}}{1+\sqrt{\theta w v(x, x_T)}} \tag{38}$$

It is reasonable to assume that the spatial component of the sensor utility $v(x, x_T)$ is qualitatively similar to the path loss from the target to the sensor $\xi(x_T, x)$. Also, for simplicity, we assume

$$v(x, x_T) = \beta\xi(x_T, x) \tag{39}$$

where $\beta > 0$ is some coefficient, then equations (37) and (38) take the following forms respectively:

$$\lambda = (k/\eta)\,p\xi(x, x_D) - [\beta\theta w\xi(x_T, x)]^{-1/2} \tag{40}$$

$$\lambda = (k/\eta)\,p\xi(x, x_D)\frac{\sqrt{\beta\theta w\xi(x_T, x)}}{1+\sqrt{\beta\theta w\xi(x_T, x)}} \tag{41}$$

Considering equations (40) and (41), the following qualitative conclusions can be driven. The optimal sensor location $x = x^{opt}$, which maximizes (40) or (41), is determined by the trade-off between path loss from the target to the sensor $\xi(x_T, x)$ and from the sensor to the destination $\xi(x, x_D)$. The optimal sensor location $x = x^{opt}$ depends on the terrain through the path loss. Increase in the transmission power p moves the optimal sensor location $x = x^{opt}$ "closer" to the target and "farther" from the destination since power increase enhances communication and allows sensor to concentrate on obtaining information from the target.

5 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 controlling sensors position. Given sensor locations, cross-layer network optimization allocates resources and configures protocols to ensure delivering the highest utility of the sensor information to the intended recipient(s). Controlling sensor location further enhances this utility.

Future efforts should address numerous research and implementation challenges, including quantification of sensor utility and utility production. Also, a simulation platform is currently under construction to further evaluate the performance of such networks in case of large number of nodes.

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