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Sensor grid resource management: Model and implementation issues

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ABSTRACT

This paper studies optimal sensor resource management in sensor grids. We formalize the problem using nonlinear optimization theory, which incorporates sensor resource constraint, energy, and expense budget. The paper also presents a pricing-based iterative algorithm for sensor management which balances the sensor user' QoS requirements to achieve a sensor system optimization based on the preference of the sensor service users. The paper discusses implementation issues of sensor management. Simulations reveal that the proposed sensor management algorithms can obtain better performance than a previous approach.

1. Introduction

A grid computing paradigm can be extended to include the sharing of sensor resources in a sensor network [1]. Sensor grids extend the grid computing paradigm to the sharing of sensor resources in wireless sensor networks. A ensor grid may combine real time data about the physical environment with vast computational resources derived from the grid architecture. By combining the complementary strengths of sensor networks and grid computing, sensor grids can support applications that require real-time information from the physical environment and a vast amount of computational and storage resources. Examples for these include environment monitoring with prediction and early warning of natural disasters, and missile detection, tracking and interception. One of the major challenges in the design of the sensor grid is how to efficiently schedule sensor resources to user jobs across the collection of sensor resources in a sensor grid [2–5].

The data for these distributed sensor services come from small devices capable of sensing physical phenomena, performing computing tasks, and communicating their results to other devices; these sensing devices formed by wireless sensor networks can be integrated into a grid environment [12,13]. Sensor devices such as video cameras, infrared sensors and microphones are being widely exploited in grid applications. For example, these are applications used in surveillance cameras in stores or fixed point cameras showing traffic flow, but the sensor data are available only to the respective owners and selected employees. A sense grid is used to enable people to share sensors in a wide-area network. The goal of the sensor grid is to allow people to access actual sensor data in the same way that they access the traditional grid environment.

There are mainly two approaches for sensor grid deployment: the centralized approach and the distributed approach [14]. In the centralized one, sensor nodes and sensor networks are connected directly to the grid. High-speed communication links are necessary for this approach where all computational tasks take place on the grid. The main drawback of this approach is the fact that it leads to excessive communication among the nodes which rapidly depletes the batteries resulting in network partitioning, a rather undesirable choice. The distributed approach is a more robust and efficient technique since it allows all computational and decision-making jobs to be performed within the sensor network according to its resources and capabilities [17].

The contribution of this paper is as follows. This paper studies sensor management in sensor grids. We formalize sensor management using the nonlinear optimization theory, which incorporates sensor service constraint, energy, and expense budget. The paper also presents a pricing-based iterative algorithm. Simulations reveal that the proposed sensor management algorithms can obtain better performance than the previous approach. The paper also discusses implementation issues of the sensor grid service.

The rest of the paper is structured as follows: Section 2 discusses the related work. Section 3 presents optimal sensor resource management in sensor grids. Section 4 discusses implementation issues of sensor management. In Section 5 experiments are conducted and discussed. Section 6 gives the conclusions of the paper.

2. Related work

There are some bodies of work aimed at studying the sensor grid system and resource management. Fox et al. [6] proposed a

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collaborative sensor grid framework to support the integration of a sensor grid with collaboration and other grids. The framework includes a grid builder tool for discovering and managing grid services and remote, distributed sensors. It provides a real-time collaborative client to enable distributed stakeholders to have a consistent view of the displayed sensor streams. The authors illustrated the versatility of the framework by constructing a robot-based customizable application for shared situational awareness. Based on the semantics-based service-oriented model, Lim et al. [7] aimed to build large-scale sensor grid infrastructure that could seamlessly integrate heterogeneous sensor resources from different projects distributed across a wide geographical area. Lu et al. [8] introduced the concept of an Internet-based Virtual Computing Environment (iVCE), which aims to provide Cloud services using a dynamic combination of data centers and other multi-scale computing resources on the Internet. Rao et al. [9] identified service requirements for the sensor grid to efficiently process data using grid technology and also proposed an end-to-end adaptive and reconfigurable resource manager for wireless sensors using grid technology to enable resource constrained sensor nodes to connect with the grid. Avil′es-L′opez et al. [10] proposed TinySOA, a service-oriented architecture that allows programmers to access wireless sensor networks from their applications using a simple service-oriented API via the language of their choice. YuJie et al. [11] described the architecture of a wireless sensor grid and also designed a connecting platform named MPAS. The advantage of MPAS is that it is based on the Web service resource framework, with the ability to integrate multiple sensor networks with the grid; also it can actuate the sensor network and support interoperability among multiple sensor networks. Li et al. [15] proposed Armada, an efficient range query processing scheme, to support delay-bounded single-attribute and multiple-attribute range queries.

3. Sensor grid resource management

3.1. Model formulation

Given below are the notations used in the following sections:

s_i^j: the sensor service allocated to sensor grid applications i by sensor service provider j
E_i: the limited energy budget of sensor grid application i
B_i: the expense budget of sensor grid application i
e_i^n: the energy dissipation caused by sensor grid application i's nth job
Sc_j: the capacity of sensor service provider j
er_i^n: the energy consumption rate
t_i^n: the time taken by the ith sensor grid application to complete nth job
T_i: the time limits given by the ith sensor grid application to complete all jobs
u_i^j: the money paid to the sensor service provider j by sensor grid application i
q_i^n: the size of the sensor grid user's nth job
p_j: the price of the sensor service provided sensor service provider j.

There is an inherent conflict in the design goals for balancing all QoS factors of the sensor grid. In modeling the QoS requirements of the sensor grid user, each sensor grid user is assumed to associate a number of QoS requirements with its sensor grid user. Each q_i^l is a finite set of quality choices for the ith sensor grid user's lth QoS dimension; let M denote the number of QoS requirements of the sensor grid user i. $q_i^1, q_i^2, \ldots, q_i^M$ represents the QoS dimensions associated with the sensor grid user i. $q_i = [q_i^1 \ldots q_i^M]$ defines an M dimensional space of the QoS choices of the sensor grid user i. Associated with each QoS dimension is a utility function, which defines the sensor grid user's benefit in choosing certain value of QoS choices in that dimension. Formally, the utility function associated with the lth QoS dimension of the sensor grid user i is $U_i^l(q_i^l)$. One-dimensional utility functions can express sensor grid user' benefits in individual QoS dimensions, but multi-dimensional QoS requirements are used to evaluate the overall benefits of the sensor grid users. Multi-dimensional QoS requirements can be formulated as a sum of each dimensional QoS utility function. The utility function associated with the sensor grid user application i is denoted by $U_i(q_i)$; the function $U_i(q_i)$ can be defined as the sum of $U_i^l(q_i^l)$. The utility of the sensor grid system U_{system} is defined as the sum of sensor grid user utilities.

We formalize sensor management using the nonlinear optimization theory, which incorporates expense budget, energy budget and a deadline.

$$MaxU_{system} \tag{3.1}$$

$$\text{Subject to } Sc_j \geq \sum_i s_i^j$$

$$\sum_{n=1}^{N} e_i^n \leq E_i$$

$$B_i \geq \sum_j u_i^j$$

$$T_i \geq \sum_{n=1}^{N} t_i^n$$

Eq. (3.1) is the sensor grid system utility maximization formulation. The utility is defined as the sum of utilities for all sensor grid applications. The overhead cost accrued to complete sensor jobs cannot exceed the expense budget B_i. The time for completing all jobs of the sensor grid application i cannot exceed the deadline T_i. The total energy consumed by all jobs of the sensor grid user i cannot exceed the energy budget E_i. The aggregate sensor service units do not exceed the total sensor service Sc_j.

The energy consumption rate of each sensor node in the system is measured by Joule per unit time. Let e_i^n be energy dissipation caused by sensor service user i's nth job and t_i^n be the execution time of job n on the sensor grid node. We denote the energy consumption rate of the sensor node when it is active by er_i^n. It is assumed that there is a limited energy budget for the sensor service user i in the system, denoted by E_i.

Let us consider the Lagrangian form of an energy constraint grid resource scheduling optimization problem:

$$L(\lambda_i, \beta_i, \phi_i, \gamma_i) = \sum_i U_i - \lambda_i\left(\sum_j u_i^j - B_i\right) - \beta_i\left(\sum_n t_i^n - T_i\right) - \phi_i\left(\sum_n e_i^n - E_i\right) - \gamma_i\left(\sum_i s_i^j - SC_j\right) \tag{3.2}$$

where λ_i, β_i, and γ_i are the Lagrangian multipliers of the sensor grid application i. Thus, given that the sensor grid knows the utility functions U_i of all sensor grid applications i, this optimization problem can be mathematically tractable. However, in practice, it is not likely to know all the U_i, and it is also infeasible for the sensor grid environment to compute and allocate sensor services in a centralized fashion. Solving the objective function $MaxU_{system}$ requires global coordination of all the sensor grid applications, which is impractical in a distributed environment such as the sensor grid.

The system model presented in (3.1) is a nonlinear optimization problem with N decision variables. The sensor service allocation solves problem (3.1) if and only if there exists a set of non-negative shadow costs $\{\gamma_i\}$. In order to reduce the computational complexity, we decompose the utility optimization problem (3.1) into two

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