Real-time Embedded Networked Sensing Design for Source Identification

Juyoul Kim and Thomas C. Harmon*
FNC Technology, Bldg.#135, Seoul National University, San56-1, Shilim9-dong, Gwanak-gu, Seoul, 151-742
*University of California, Merced, P.O. Box 2039, Merced, CA 95344
gracemi@fnctech.com

1. Introduction

Embedded networked sensing (ENS) technology is rapidly expanding into environmental application domains, where network coverage issues are tightly coupled to the environmental media and observational objectives. The goal of this work is to develop and test an automated, real-time ENS coverage design algorithm in the context of an environmental simulation model. The algorithm combines the application of a genetic algorithm (GA) with a deterministic inverse modeling approach, and is demonstrated in the context of a bench-scale groundwater test bed in which the ENS objective is to identify the location of a heat source. More specifically, optimal sensor locations are determined in real-time using a GA-based evolution algorithm whose objective function is the trace minimization of the model-prediction covariance with respect to potential sensor locations. Next, measured temperature sensor data and a descent-based inverse technique are used to update the source location estimate. The procedure is repeated until a pre-determined sensor supply is exhausted. The transient heat transport experiment is undertaken in which sources placed upstream of a manually configurable ENS comprising thermocouples for mapping spatio-temporal temperature distributions. The ENS approach successfully corrected an erroneous initial source location estimate and incrementally improved upon this estimate with the addition of new sensors.

2. Experimental Design Algorithm and ENS Test Bed

The goal of ENS design is to identify the optimal sampling sets from among many potential sensor locations. Given a model for the physical system in which the ENS is to be deployed, the ENS design problem can be expressed as an optimization problem employing an integer programming formulation. More specifically, the ENS design problem is to identify sensor locations which minimize the trace of the model-prediction covariance:

$$\text{min trace Cov}(\mathbf{p}) \tag{1}$$

$$\text{subject to } \sum x_i C_i = B \tag{2}$$

where $\mathbf{p}$ is model parameter vector to be estimated, x_i is the indicator variable associated with sampling i, $x_i=1$ if sampling i is selected; 0 otherwise, B is the budget, and C_i is the cost of sampling I. Here the covariance matrix provides a quantitative measure of the reliability of model parameters and can be used to evaluate and compare alternative ENS deployment strategies. The reliability of the estimated parameters is characterized by a norm of the covariance matrix. Covariance matrix of the estimated parameters is given as:

$$Cov(\mathbf{p}) = \frac{E(\mathbf{p})}{M-L}\left(\mathbf{J}_D^T \mathbf{J}_D\right)^{-1} \tag{3}$$

where E is the least squares error, M is the total number of observations, L is the parameter dimension, and $\mathbf{J}_D$ is the Jacobian matrix.

The experiment was performed in a three-dimensional intermediate-scale physical groundwater test bed. The test bed consists of a 1.5×0.5×0.4 m glass tank containing a water-saturated sandy porous medium as shown in Figure 1. Framed stainless steel screening is used to fabricate constant head boundaries at the influent and effluent ends of the tank. Steady, unidirectional flow through the sand is achieved by constant peristaltic pumping into the influent clear well (Masterflex® Model 7420, Cole-Parmer, Vernon Hills, IL), while maintaining constant head conditions in the effluent clear well using a weir. The model groundwater system is packed with homogeneous, clean sand (nominal grain diameter 0.33 mm, Lonestar Sand, Monterey, CA). The sandy medium is saturated with water to an average depth of 12 cm. The final porosity and bulk density of the model aquifer are determined to be 0.38 and 1.60 g/cm^3. The heat source is introduced at a fixed location as a continuous 31.6 mL/min source of warm water via the same peristaltic pump equipped with small precision tube (1.6 mm i.d., Masterflex® L/S™ 14). Seventeen thermocouples (J type, 1.5 mm o.d.) are deployable in positions indicated in Figure 1 to monitor three-dimensional temperature distributions resulting from point source injection. Two thermocouple is fixed to the outlet of the warm water injection tube to monitor the source temperature, which was relatively constant.

3. Results and Discussion

The release of the warm water stream results in the propagation of a 3D quasi-Gaussian 3D temperature distribution in the groundwater flow direction. Sensors placed downstream exhibit the arrival of a dispersed temperature front which builds to a steady response. In order to use the mathematical heat transport model in the context of the ENS design problem, key parameters which cannot be independently estimated must be determined through model calibration. It is important to emphasize that this calibration step is a necessary and important step in most environmental modeling efforts. The reason for this is that in spite of the fact that the physical transport of mass and energy in environmental systems are reasonably well-understood, environmental media (and the associated model parameters) are typically comprised of distributed properties which are difficult to independently determine. A nonlinear least squares regression algorithm was employed to estimate the thermal dispersion coefficients for the test bed sand-water system as $K_x = 0.6$ cm^2/min and $K_y = K_z = 0.48$ cm^2/min by fitting the analytical solution to the transient temperature values observed at the prefixed location of x=65 cm, y=25 cm, and z=8 cm for the flow velocity of 7.8 cm/h. The real-time sequential ENS design procedure is demonstrated for the cases of 2, 4, 6, and 8 sensors, respectively. For each of these figures, the plots exhibit the GA-determined sensor locations, the L-M-based source prediction (from the perspective of the x-y and x-z planes), and a comparison of the simulated and observed temperature histories at the determined sensor locations. The resulting progression of the ENS design alternates between locations directly downstream of the source and symmetrically arranged off-center sensors. As more sensors are added, the same pattern propagates downstream. As expected, this behavior suggests that, for a steady-state temperature distribution, the best sensor network characterizes the gradient some optimal distance downstream of the source. As these locations become occupied, subsequent choices are forced downstream where the gradient is less sharp and therefore contributes less to the source delineation effort.