A SOIL MOISTURE SMART SENSOR WEB USING DATA ASSIMILATION AND OPTIMAL CONTROL: FORMULATION AND FIRST LABORATORY DEMONSTRATION

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ABSTRACT

We have developed a new concept for a smart sensor web technology for measurements of soil moisture that include spaceborne and in-situ assets. The objective of the technology is to enable a guided/adaptive sampling strategy for the in-situ sensor network to meet the measurement validation objectives of the spaceborne sensors with respect to resolution and accuracy. One potential application is the Soil Moisture Active/Passive (SMAP) mission. The science measurements considered are the surface-to-depth profiles of soil moisture estimated from satellite radars and radiometers, with calibration and validation using in-situ sensors. Installing an in-situ network to sample the field for all ranges of variability is impractical. However, a sparser but smarter network can provide the validation estimates by operating in a guided fashion with guidance from its own sparse measurements. The feedback and control take place in the context of a dynamic data assimilation system subject to energy and accuracy constraints. The overall design of the smart sensor web including the control architecture, assimilation framework, and actuation hardware are presented in this paper. We also present results of initial numerical and laboratory demonstrations of the sensor web concept, which includes a small number of soil moisture.

***Index Terms*—** sensor webs, soil moisture, calibration and validation.

1. INTRODUCTION

The long-term vision of Earth Science measurements involves sensor webs that can provide information at conforming spatial and temporal sampling scales, and at selectable times and locations, depending on the phenomena under observation. Each of the six strategic focus areas of NASA Earth Science (climate, carbon, surface, atmosphere, weather, and water) has a number of measurement needs, many of which will ultimately need to be measured via such a sensor web architecture. Here, we develop technologies that enable key components of a sensor web for an example measurement need, namely, soil moisture. Depending on the particular application area, soil moisture may need to be measured with a number of different sampling characteristics. It is therefore necessary to develop sensor web capabilities to enable flexible and guided sampling scenarios, as well as calibration and validation strategies to support them. This project seeks to develop and demonstrate, via numerical and laboratory experiments, the architecture and algorithms for a sensor web control system that interconnects the elements of the web and enables "smart sensing" through the integration of a data assimilation framework [1] subject to constraints derived from accuracy requirements and energy limitations. The sensor nodes will be guided to serve as a macro-instrument compatible with the large-scale effective measurements by satellite sensors.

2. THE SENSOR WEB CONCEPT

The ground footprints of remote sensors are often coarser than the scale of variations of the variables. As a result, the remote sensing estimate is only a coarse-resolution estimate of a field mean. In-situ sensors often sample a point location in the heterogeneous field. Statistics of errors of retrieval are indicative of errors in measurements, and errors in representativeness of in-situ samples. These two errors cannot be separated using existing sampling networks.

For soil moisture profile fields, for example, the total variability is derived from variability in processes that influence it on a wide spectrum of scales ranging from meters to several kilometers. A key challenge is how to calibrate and validate the satellite footprint estimate, for example from SMAP, which is an average of the field that may be 10s or 100s of km^2 for the radar and radiometer, respectively. To install an in-situ sensor network that samples the field across all ranges of variability is impractical and cost-prohibitive. Our hypothesis is that a much smaller but smarter network can provide the needed validation estimates for satellite measurements.

The sensor web has to operate in a guided fashion. The guidance comes from the sparse measurements themselves, which, through a control system, guide the sensor web to modify the sampling rate and other parameters such that their observations yield the most representative picture of the satellite footprint conditions. The control and feedback take place in the context of a data assimilation system that merges data from forecast models, sensors, and relevant auxiliary information to produce the best estimate of the variable field and its anticipated evolution, balanced against measurement costs. This means that even if a measurement may improve the value of the soil moisture estimate, if it is too costly in term of power usage, the optimal decision could be not to take that measurement. Here, we develop and demonstrate this control system for guided sampling by a sensor web. The guidance is towards producing representative and statistically unbiased estimates of the remote sensing footprint variable estimate based on a finite-size sensor web with dynamic operations. The duty cycle and sampling at the network nodes will be driven by a data assimilation system that can provide guidance on the worth of each measurement at different sampling intervals. Uncertainty in the model and current estimates can form the basis for the quantitative evaluation of the worth of data at each node.

The instruments operating at an in situ node could include meteorological sensors (temperature, precipitation, wind, solar radiation, etc.), soil moisture probes installed on surface and at varying depths, and multifrequency tower-mounted radars for O(100)m observations of soil moisture profile fields. Ancillary data such as topography, vegetation cover, and soil texture could also be provided at the spatial scale of in situ observations. A block diagram depicting the interrelationships of the elements of the proposed system is shown in Figure 1.

3. APPROACH

3.1. Data Assimilation

Data assimilation is a statistical estimation framework that combines physics-based model forecasts with observations [1. In data assimilation it is assumed that models have uncertainty. It is also assumed that observations have errors. The relevant measures of the probability density function of the model forecasts are propagated in time until measurements are available. The probability density function or measures of it are updated based on the relative uncertainty of model forecasts and observations. The data assimilation and the sensor web will be coupled through an optimal control system. The duty cycle and weight given to each node measurement is evaluated against the value of that measurement in the data assimilation system. This information is passed on to the control system to dynamically adjust the sample averaging and data collection. Data assimilation has to take place in the context of a time-evolution model describing the physical process of soil moisture variations. The time and depth evolution of soil moisture fields can be expressed via a pair of coupled partial different equations (PDE) in space and time. This model has a number of parameters associated with terrain and meteorological conditions. The solution to the coupled differential equation is an estimate of future states of soil moisture fields with the knowledge of the current state and the model parameters. The Soil-Water-Atmosphere-Plant (SWAP) model [4] is a community standard solver for such a model, and has been used here to develop a time-series of soil moisture variations using actual values of rainfall measurements for sample areas.

3.2. Control Architecture

The physics-based models have uncertainty and observations have errors. Thus, we model soil moisture at any point location in a spatial field as a discrete time stochastic process $\{X_t, t = 0,1,2,...\}$, the evolution of which is described by a stochastically forced hydrologic model. At specified times that maximize the information content of a measurement, each sensor can be activated to sense and transmit information. At any time t the coordinating center utilizes the information it has gathered up to t to estimate field mean and to specify the mode each sensor will employ at time $t+1$, so as to gather additional data. Thus, the objective is to determine: (i) a sensor mode selection strategy for the coordinating center; (ii) an estimation strategy for the coordinating center; and (iii) real-time encoding strategies for the sensors [2]. We have established a common mathematical framework and terminology for the control architecture in the context of other elements of the sensor web as shown in Figure 2. Fundamental issues in selecting a sensor configuration are:

- Energy consumption cost of current sensor configuration
- Effect on the quality of the current state estimate
- Effect on future decisions for sensor configurations and their effect on quality of future state estimates
- Trade-off between the first and last two items above

This problem belongs to the class of optimization problems known as Partially Observable Markov Decision Processes (POMDP). To solve such problems, backward induction is typically used to determine optimal sensor selection and estimation strategies sequentially in time, by moving backwards in time. The solution method has the following features:

- Compute conditional probability p_t of current state $\underline{X}_t$ using all previous measurements (and all previous sensor configurations)
- Choose optimal sensor configuration $\underline{U}_t$ and optimal estimate using p_t

Sensor selection strategy g_t and estimation strategy l_t are determined by specifying the optimal sensor configuration and optimal state estimate for every possible realization of p_t

3.3. Sensor Models

We envision a sensor web that will ultimately comprise of different varieties of sensors. In particular, the soil moisture sensors could be localized, such as probes, or could be remote, such as tower-mounted or aircraft-based radars or radiometers. Derving physics-based remote sensor models to relate their measurements to estimates of soil moisture is generally rather complicated. The in-situ sensors, on the other hand, offer an opportunity for accurate measurements that are related to soil moisture values via simple empirical models. Several standard methods of in-situ sensing exist, such as time-domain reflectometer (TDR) probes, neutron probes, capacitance probes, and ring resonators. We have chosen an in-situ soil moisture probe making highly localized measurements. We selected and procured capacitance probes from Decagon, model ECH$_2$O EC-5, and developed its calibration curve in form of a third-order polynomial. This polynomial was used as the initial sensor model input to the control system. The model generated with empirical data results in a calibration accuracy of 1%.

For remote sensors, which could be tower-mounted, airborne, or spaceborne, the physics-based retrieval models of soil moisture involve solutions to nonlinear optimization problems [3]. A number of models that relate radar backscattering coefficients to soil moisture have recently been developed (the "forward" problem). The models could be numerical or analytical. The "inverse" problem, or the retrieval problem, has also been addressed in our previous works, but needs further advancement. The basic strategy is to derive multi-dimensional polynomial expressions that are derived from the more complicated numerical models in several unknowns. The closed-form nature of the fitted model allows us to apply a number of optimization techniques, both local and global. The statistical nature of the unknowns (e.g., soil moisture and surface roughness) can be systematically included in development of the optimization algorithm.

3.4 Actuation Hardware

A key enabling technology in the proposed system is the proper actuation of the sensors using output computed by the control algorithms. Actuation allows the measurement parameters to be dynamically adjusted according to the data collected so far, the inferred soil condition, as well as the overall objective of the sensing task. This process involves the sensor radio transceiver receiving the control message from the coordinating center, decoding the message into a set of parameter values associated with the measurement. Commonly available sensor platforms for R&D purposes, e.g., the MICA2 motes, often lack sophisticated actuation capabilities. The typical actuation on these platforms is limited to setting data sampling rate and specifying the duty cycling rate of the sensors. The proposed system involves the dynamic tuning of a wide range of parameters representing various modes of each instrument. For this development, we will leverage the existing Narada board already developed by a colleague at the University of Michigan [4].

4. LABORATORY TESTBED

The control signals generated by the central coordinator need to be conveyed to the sensors via wireless links and actuators at the sensor locations. The objective of the laboratory test-bed is to provide experimental proof-of-concept for the actuation of sensors, given the control signal and antecedent sensor data that are available to the coordinator via wireless links. We have planned two major phases for the actuation experiments (phases A and B). In Phase A, recently completed, COTS devices were used for actuation and wireless communication. The control feedback loop was implemented to command a single sensor at a single location via an actuation device. The control policy for the 1-D problem was successfully integrated with the lab set up and used to actuate the sensor at intervals prescribed by the control algorithm.

In Phase B, custom actuation and communication devices will be built (possibly using some COTS components). Furthermore, in parallel with the control algorithm progress, multiple sensors will be included in the demonstration, each of which can be controlled by the coordinator. Phase B will also include optimization criteria for power management. Phase A experiments were in the laboratory only. In Phase B, we plan to set up a field-analog experiment, where both in-situ and remote sensors may be used, each of which will receive commands from the coordinator and actuated accordingly. Each sensor can in turn send its data back to the coordinator.

5. SUMMARY

The proposed technology for coupling a data assimilation framework into a sensor web control system to achieve an optimal dynamic sampling strategy is fundamentally new. Previous studies related to this topic exist, but have used an empirical approach to search for temporal stability of network nodes for capturing the mean conditions of the observed field [18]-[19]. No previous work has been done to implement such dependencies within a control system to guide the sampling of a sensor web. The novel aspects and benefits of this technology are:

- It uses a physics-based approach to relate the variations of soil moisture to soil texture, terrain, vegetation, and meteorological conditions, and hence the decisions on weighting the node measurements are solidly tractable, regardless of geographic location.

- It enables, for the first time, a dynamically guided sampling strategy for the sensor web by integrating in situ data, real-time processing, data assimilation, and an optimal control algorithm. The new sampling strategy enables representative estimates of the time-varying field mean provided by space-based remote sensing assets.

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6. REFERENCES

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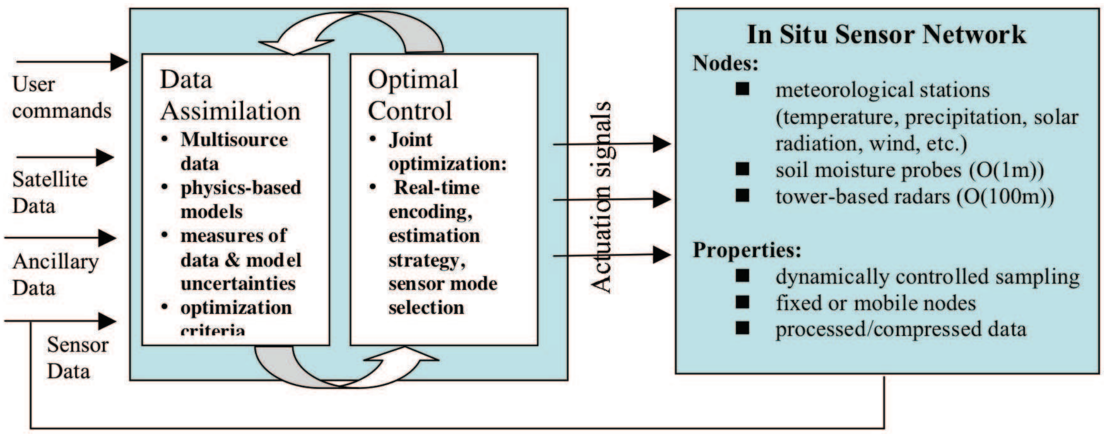

Figure 1. Elements of the sensor web technology and their interrelationships. The semi-closed system generates guidance to the sensor web, through actuators, for modifying its sampling characteristics using a coupled data assimilation and control system, antecedent sensor data, and ancillary data (e.g., topography and soil texture). User command can also be incorporated.

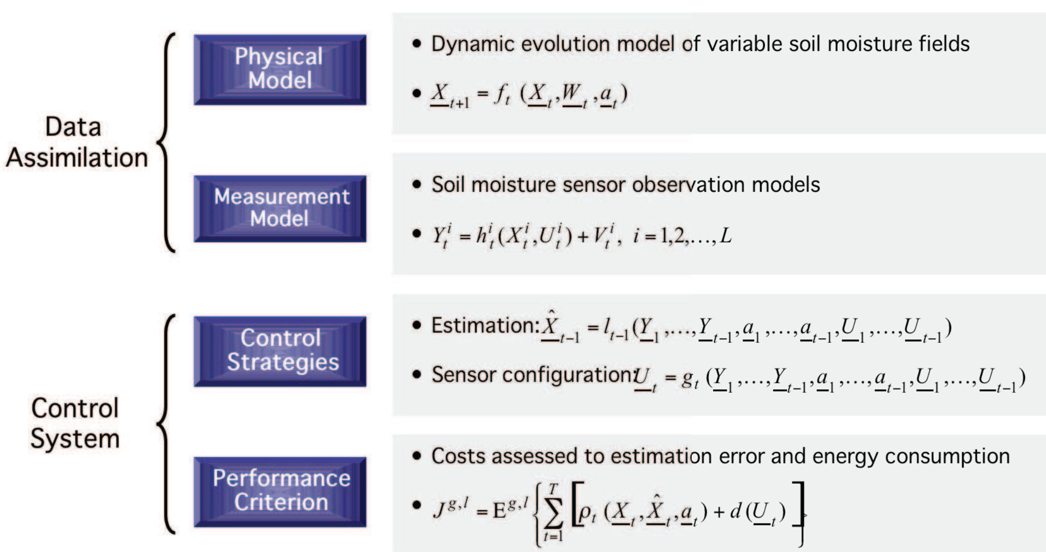

Figure 2. Overall problem formulation and mathematical notation, showing the relationship between the different project components.