Integrating Data Assimilation and Optimal Control for Enhancing Sensor Web Architectures

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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. An example we have used previously is soil moisture, perhaps the most commonly needed variable in the strategic focus area roadmaps. Depending on the particular application area, this quantity 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. The architecutre and algorithms for a sensor web control system need to be developed, therefore, that interconnect the elements of the web and enable “smart sensing” through the integration of a physics-based data assimilation framework, as shown in Figure 1. 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 remote sensing and retrieval and error 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. This broad spectrum of variability and multiple causes is not unique to soil moisture but is a characteristic of many Earth system variables. A key challenge is how to calibrate and validate the satellite footprint estimate, an average of the field that may be 10s or 100s of km^2. To install an in-situ sensor network that samples the field across all ranges of variability is impractical and cost-prohibitive. The hypothesis of this class of concepts 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 based on physical models.

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 conditioned current estimates can form the basis for the quantitative evaluation of the worth of data at each sensor web node. Dynamic commanding and data ingestion from those nodes optimize the value of the sparse ground-truth network in validating the remote sensing-based coarse-resolution retrieval. The remote sensing instruments could produce observations at km-scale. 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.

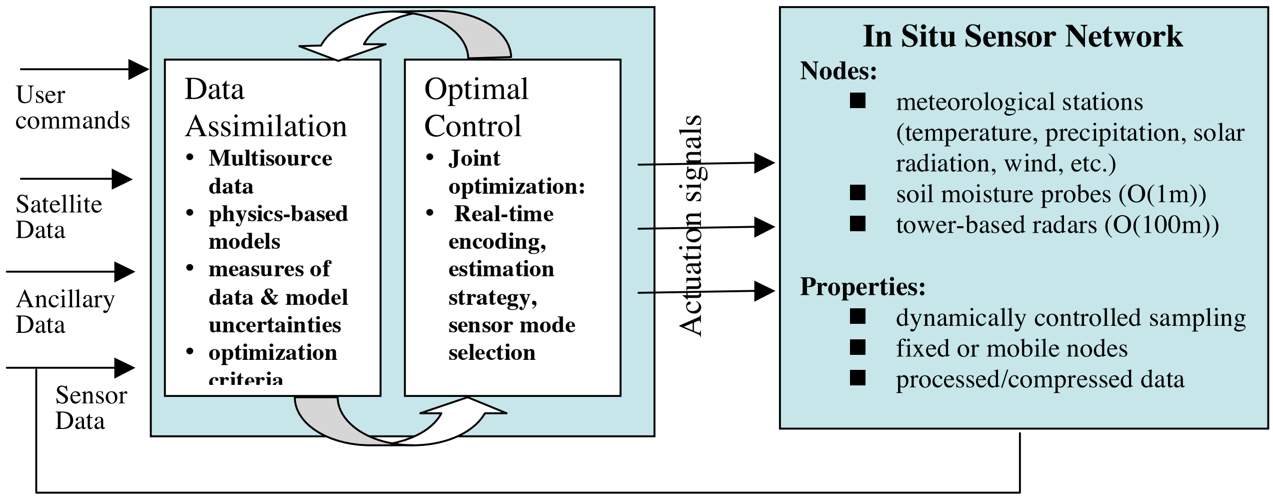

Figure 1. Elements of the sensor web technology and their interrelationships. The semi-closed system generates guidance to the sensor web, through actuators, for modifying its sampling characteristics using a coupled data assimilation and control system, antecedent sensor data, and ancillary data (e.g.,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

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. 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 such 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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