Virtual Sensor-Powered Spatiotemporal Aggregation and Transformation: A Case Study Analyzing Near-Real-Time NEXRAD and Precipitation Gage Data in a Digital Watershed

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ABSTRACT
In this paper, we describe the case for creating and managing "virtual sensors" for near-real-time sensor data aggregation and transformation with a case study in a watershed near Chicago. We explore various levels of abstractions of "virtual sensors", and how the virtual sensor concept and digital watershed tool can help facilitate community participation and build consensus on using and re-purposing the near-real-time data. We describe our proposed approach on aggregating NEXRAD data and on-ground *in-situ* precipitation gage data in near-real-time for anomaly detection purpose.

Keywords
Virtual sensor, NEXRAD, precipitation, gage station, reuse, repurpose, spatiotemporal aggregation and transformation, digital watershed, sensor web

1. INTRODUCTION
Physical, chemical and biological sensor networks have been used and are increasingly being deployed for measuring various environmental conditions and processes. For example, the National Weather Service (NWS) Next Generation Weather Radar (NEXRAD) system has been operational since 1997 providing meteorological observations that have been used for weather forecasting [Fulton *et al.*, 1998]. Recent advances in cyberinfrastructure technologies are allowing researchers to use large quantities of heterogeneous sensor data for furthering the understanding of large-scale environmental processes, as well as in monitoring and modeling the quality of the environments in which the sensors are deployed [Liu *et al.* 2007].

In their endeavors, researchers often seek the "raw" sensor data in order to ensure that their analyses will be free from bias, but usually such data has already been processed in certain ways. Such situations demand the repurposing of sensor data which might be beyond the scope of the original sensor design and deployment. Similar to the recent revolution of computer server virtualization (or virtual machines) [Oguchi and Yamamoto, 2008], it is now necessary to consider virtualization of sensors and sensor networks so that existing deployments of sensor networks and their measurements can be easily repurposed and used in new ways. This paper will explore the levels of virtual sensor abstraction and discuss acceptance of certain data quality control methods, coordinate transformations, measurement fusion and aggregations. A case study on aggregating NEXRAD data and on-ground *in-situ* precipitation gage data in a digital watershed is presented. Discussions on the process of validating virtual sensors through community participation and review are also presented, as are implications for national environmental observatories such as the WATERS Network.

2. RELATED WORK
The concept of "Virtual Sensors" can be found in quite diverse bodies of literature. For example, "virtual sensors" have been defined as new predictions or higher-level concepts based on applying machine learning or artificial intelligence methods to multiple original sensor signals [see, *e.g.*, Ibargüengoytia and Reyes 2006; Persson *et al.* 2007, Peńarrocha *et al.* 2006]. In the wireless sensor network domain, "virtual sensor" observations are based on computation or aggregation of in-network sensor measurements. Such computation is usually based on standard SQL aggregation queries such as MIN, MAX, or SUM (see, *e.g.*, Global Sensor Network (GSN) by Aberer *et al.* 2007). "Virtual sensors" are also used in feedback-control applications along with "virtual actuators" [Ciciriello *et al*. 2006]. A "virtual sensor network" is also proposed to dynamically reconfigure sensor nodes for different purposes [Jayasumana *et al.* 2006].

The definition used by Kabadayi *et al.* [2006] is most closely related to the use of virtual sensors in this paper, where heterogeneous physical sensor data are abstracted through software aggregation. Their paper focuses on the development of virtual sensor Application Programming Interfaces (APIs), but does not offer a discussion on the levels of acceptable error corrections, and spatial-temporal scale transformations. Additionally, they did not discuss the community approach to virtual sensors, and how virtual sensors can facilitate broad community collaborations. Furthermore, their application is construction management, not environmental management and monitoring.

3. EXPLORING VIRTUAL SENSORS AND A PROTOTYPE DIGITAL WATERSHED

As a practical example of virtual sensors, a paragraph on page 108 of the recently released WATERS Network Science, Education, and Design Strategy (SEDS) Draft report [WATERS Network, 2008] reads as follows: "*Signals from arrays of individual sensors and clusters of such arrays would be combined to provide higher-level information. For example, an array of soil moisture and temperature sensors might be coupled to a microclimate array to provide a* ***virtual*** *soil moisture flux* ***sensor***". This clearly describes the relationship between a virtual sensor and a physical sensor, that is, aggregations among physical sensors through certain computations.

Since environmental processes and phenomena are inherently spatiotemporal and noisy, we explore the concepts of virtual sensors through these increasing levels of processing below.

3.1 Error correction and QA/QC filtering

Many government agencies provide sensor data after their extensive error correction and automatic quality analysis and quality control (QA/QC) methods. One example can be found in NEXRAD data where over 10 error corrections and QA/QC filtering steps occur during Stage I processing of the precipitation data [Chrisman *et al.,* 1994; Fulton *et al.,* 1993]. We consider data processed in this way to be our first level of virtual sensor data. The question for the broad community that will likely use such data is whether such extensive error correction is desirable to individual researchers.

3.2 Spatiotemporal coordinate transformations

One commonly encountered task in environmental virtual sensor transformations is coordinate transformation, both spatially and temporally. Spatiotemporal coordinate transformation is well understood in the GIS community (see, *e.g.*, Open Geospatial Consortium Coordinate Transformation Services [Open Geospatial Consortium, 2001]; ISO ISO 19108:2002 Temporal Schema [ISO 19108, 2002]; ISO 19107:2003 Spatial Schema [ISO 19107, 2003]). For example, World Geodetic System 1984 (WGS-84) (used for GPS location) usually needs to be transformed to a local plane coordinate system since most physics-based environmental models use grids on a local plane. Typical calendar transformations include Julian calendar to Gregorian calendar conversion or vice-versa.

3.3 Spatiotemporal measurements aggregations

Simple aggregation such as wind vectors can be easily derived by combining wind direction and magnitude into a new form of virtual sensor data.

More complicated measurement aggregations such as up- and down-scaling sensor measurements and merging data from multiple sensors with different spatiotemporal support (*i.e.* the region in space and/or time that the measurement represents) are more difficult to perform.

Upscaling measurements refers to the process of increasing the region in space and/or time that a particular measurement represents. Because environmental processes are highly variable in space and time, the upscaled region is often larger than the scale of the variability, and thus corrections must be made to account for effects of sub-scale fluctuations at the upscaled measurement scale (*e.g.* stochastic methods [Rubin, 2003] or spatial filtering [Beckie *et al*., 1996]). Conversely, downscaling measurements refers to reducing the region in space and/or time that the measurement represents. Again, this process is not straight-forward when the process being measured varies at spatiotemporal scales smaller than the original measurement. Finally, merging sensor data with different spatiotemporal support requires both up/donwnscaling and a relationship between the sensor measurements which takes into account their correlations and the expected measurement error of each sensor. For example, the Multi-sensor Precipitation Estimator (MPE) measurements (discussed in Section 4) merge rain gage data (point spatial support, minute temporal support, produced at a frequency of minutes to days) with radar data (~2 km^2 spatial support, point time support, produced every 6 to 10 minutes) and with infrared satellite data (~16 km^2 spatial support, point time support, produced every 15 minutes) [Kondragunta 2007]. This merge requires scaling of the measurements in space and time and spatiotemporal interpolation such that the measurements from the different sensors reflect congruent quantities of rainfall and a relationship between the gages, radar, and satellite measurements that takes into account their measurement accuracy.

Note that certain aspects of the above-discussed virtual sensor abstractions are sometimes called "data ingest" process in some sensor web literatures (see e.g., Balazinska et al., 2007), which refers to "calibrate, gap-fill, regrid process". However, the spatiotemporal measurement aggregation level of the virtual sensor is far more complex than simple interpolation or regridding, as discussed above.

By adopting the concept of virtual sensors and providing tools to create and share virtual sensors, a higher level community participation and collaboration can be achieved. A virtual sensor created by one researcher could be used by another researcher to test different hypotheses such as new data transformations (e.g. Battan, [1973], Smith and Krajewski [1993], and Morin *et al.* [2003] discuss different transformations from measured NEXRAD radar reflectivity to rainfall rates) or to use similar data in updated models. This re-use can build acceptance of certain processing steps for new or existing sensors.

A prototype digital watershed tool is being built to allow us to experiment with various levels of virtual sensors for the case study presented in section 4. At the core of the prototype digital watershed is a light-weight virtual sensor middleware (written in python programming language), which has the capability to perform lightweight in-memory near-real-time data retrieval, transformation and aggregation (which we call filters, such as converting ESRI shapefile to KML (Keyhole Markup Language) file), metadata extraction from KML files, and interfacing with more computationally intensive workflow-based tasks. A Google Map-based web user interface can show different KML files as different data layers and also allow users to contribute data by submitting new KML files. The idea of using KML is similar to the one proposed in ObsKML [2008]. From the end user perspectives, each KML file could represent a new virtual sensor (although we should exclude those nonchangable geographical objects such as sensor stations or watershed polygons etc.). KML has recently been approved as one of the OGC standards [OGC KML, 2008]. Note that data streaming middlewares such as RBNB [Tilak et al., 2007] could be integrated and used to perform the data streaming task in the future, although that is not the focus of this paper.

4. A CASE STUDY

In this case study, we discuss the development of a virtual sensor for precipitation in the Salt Creek Watershed, which is located in the greater Chicago region in Illinois. In the following sections, information and issues related to NEXRAD and precipitation gages in Salt Creek are presented, followed by a detailed description on how to create a virtual precipitation sensor.

4.1 NEXRAD

The NEXRAD system is composed of approximately 160 radar sites located throughout the United States and selected overseas areas. These radar sites measure reflectivity, radial velocity and spectrum width of the radar echoes returned from volumes within the atmosphere. These volumes are defined by a polar grid centered at the radar. The Radar Product Generator (RPG) creates 41 “products” from the three measurements made by each radar via calibrated transformations and (often) threshold-based QA/QC. These products represent estimates of meteorological process variables such as hourly precipitation, tornadic vortex signature, hail index, or severe weather probability. More information about the RPG is given by Klazura and Imy [1993] and Fulton *et al.* [1998]. The data from the NEXRAD system is divided into a hierarchy that indicates the increasing amount of preprocessing, calibration, and quality control performed [Klazura and Imy, 1993; Fulton *et al.*, 1998; Wang *et al.*, 2008]. Thus, these data (except in the case of Stage I, Level II as discussed below) represent virtual sensor data.

Stage I data refers to data from a single radar site, and is further subdivided into Level II and Level III data, which refer to the original three measurements made by the radar and the 41 products generated by the RPG, respectively. Stage II provides estimates of hourly rainfall accumulations that merge NEXRAD Level III data with rain gage measurements averaged over a 4 km by 4 km grid (which corresponds to the Hydraulic Rainfall Analysis Project [HRAP] grid [Fulton 1998]) [Fulton *et al.* 1998]. The rain gage data are incorporated to eliminate the mean field bias of the radar measurements [Seo, 1999], and thus, must be subjected to QA/QC before the creation of the Stage II product. Stage III refers to a mosaic of Stage II products from multiple radars that cover an entire forecasting region of a River Forecast Center. Finally, Multi-sensor Precipitation Estimator (MPE) refers to hourly rainfall accumulations that merge NEXRAD Stage III and Geostationary Operational Environmental Satellite (GOES) products [Fulton *et al.,* 2002].

The data types, and transformations used to create the Level III, Stage II and III, and MPE data, are tailored to the needs of the NEXRAD agencies. Originally, real-time access to NEXRAD data was not provided to private organizations or government agencies (outside of the NEXRAD agencies) [Klazura and Imy, 1993]. Access to a subset of the Level III data was provided via the NEXRAD Information Dissemination Service (NIDS) and the National Climate Data Center (NCDC) archives; however, since the base data (Level II) was not available, researchers could not directly transform or manipulate the raw radar measurements. For example, the RPG only produces rainfall measurements as either hourly accumulations or storm-total accumulations. If a researcher was interested in shorter duration accumulations (*e.g.* 20 min.) it would be necessary to construct these data from the Level II data. In 2001, Level III products become available though NOAAPORT and Unidata’s Information Data Distribution (IDD) project. However, these services still did not provide access to the high-resolution base (Level II) data, thus, in 2004, the Collaborative Radar Acquisition Field Test Project (CRAFT) was expanded to provide real-time access to the Level II data [Droegemeier *et al.*, 2002, NOAA News 2004]. Recently, Krajewski *et al.* [2008] presented the hydroNEXRAD prototype, a system that will provide researchers with NEXRAD Level II data at the watershed level. This system facilitates the transformation of Level II data using a set of predefined operations to achieve a customized output. It is important to note that, currently, hydroNEXRAD is not designed for near-real-time transformation and aggregation of the Level II data, nor does it allow researchers to implement their own transformations, thus increasing the set of predefined operations.

4.2 Precipitation gage station

The United States Geological Survey (USGS) has installed and maintains several tipping bucket rain gages within the Salt Creek watershed. These gages register volumes of water falling on a .03 m^2 area in 0.0254 cm increments (referred to as a tip). The tip data stream from a particular gage is sent to a programmable logic controller (PLC), which records the cumulative volume in 5-minute intervals and outputs the data using the MODBUS protocol to a spread spectrum radio. The radio sends packets of data every five minutes to the Du Page County Supervisory Control and Data Acquisition (SCADA) system which then loads the data (within 10-30 min) to an FTP server. Failed five minute transmissions are indicated with a numerical flag. The USGS automatically downloads the gage data from the FTP server, removes the data flagged as failed transmissions, and publishes them in the USGS National Water Information System: Web Interface (NWIS-web). USGS personnel visit the sensors on a regular basis and download locally logged data that is used for *post facto* QA/QC of the telemetered data, predominantly the removal of false zeros (*i.e.* failure of the sensor to measure falling rain).

After the processing by the PLC and the QA/QC performed by the USGS, the Du Page County FTP site and the NWIS-web disseminate the product of precipitation sensors.

4.3 A new virtual precipitation sensor

We propose a new virtual sensor for the Salt Creek watershed that produces measurements of 20-minute rainfall accumulations at the gage locations (with the spatial support of the gages), which merges data collected by the regional NEXRAD site (call sign KLOT) and the gages maintained by the USGS in Du Page County. Since NEXRAD precipitation observations at this spatiotemporal scale are not created by the RPG, Level II data will be required. The virtual sensor data stream will be produced via the following workflow steps:

1) Convert the Level II reflectivity to rainfall rates using the convective Z-R relationship (Fulton *et al.* 1998). This is the same relationship used to create the Level III hourly accumulation precipitation product for the KLOT radar.
2) Perform QA/QC on the radar data to remove observations below the signal to noise ratio, and range ambiguous observations. Both these types of observations are indicated by numeric flags within the Level II data.
3) Perform QA/QC on the gage data to remove failed transmissions indicated by a numeric flag in telemetered rain gage data.
4) Accumulate both the radar and gage data in time to be collocated (in time) in 20 minute intervals.
5) Map the Level II, radial local plane coordinates onto WGS-84 geodetic coordinates (used to locate the gages) to facilitate spatial interpolation.
6) Spatially interpolate the 20 minute radar rainfall estimates to collocated estimates at the gage locations.
7) Fuse the 20 minute accumulation gage and radar data using a dynamic Bayesian method as suggested by [Hill *et al.*, 2007] to produce a robust estimate of the 20 minute precipitation accumulations at the gage locations.

We are in the process of implementing the above mentioned workflow and will report the results in terms of using such new virtual precipitation sensor data for anomaly detection in subsequent paper and conference presentations.

5. CONCLUSIONS AND FUTURE WORK

This paper explores the usage of virtual sensors in near-real-time environmental sensor networks with a case study that proposes a virtual precipitation sensor in a participatory digital watershed near Chicago. We describe various levels of virtual sensors and their spatiotemporal transformations and how they are relevant to environmental observatories. Often on-the-fly transformations can be done by applying some light-weight filter operations, while more computationally intensive transformations can be done through workflow systems such as the one being developed in NCSA's TRECC project [2008]. Virtual sensors can be considered new, near-real-time sensor data sources and thus, can be reused among community researchers. Provenance-aware virtual sensors are thus important for community collaboration where different users can examine how such virtual sensors are derived. Provenance technologies are also being developed in NCSA TRECC project and we will explore such integration with the prototype system presented in this paper.

We think the concept of virtual sensors and the virtualization of sensor networks will allow diverse user communities (such as the WATERS Network environmental observatory) to access and modify sensor data and potentially even provide new virtual sensor data streams over the internet in near-real-time. This is similar to the Microsoft SenseWeb [Kansal *et al.* 2007] idea, but with an extension from physical sensors to more broadly defined virtual sensors.

Our future exploration of virtual sensors will also consider privacy filtering as another layer of transformation. The privacy issue will become evident when large-scale environmental monitoring sensor networks are coupled with citizen science-type participatory sensing [Abdelzaher *et al*., 2007; Cuff *et al.*, 2008]. For example, in the city of Chicago, we will soon have access to near-real-time consumer water usage data through smart water meters deployed at the residential household level. This demands proper privacy protection when such data are provided for environmental and water resource study.

6. ACKNOWLEDGMENTS

Our thanks go to UIUC/NCSA AESIS (Adaptive Environmental Sensing and Information Systems) initiatives for funding support and NCSA TRECC year-8 project funding support. The authors also thank Seong-Gon Kim for helping the prototype implementation.

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