Challenges in supporting extraction of knowledge about environmental objects and events from geosensor data

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ABSTRACT: Technologies for capturing large amounts of real-time and high-detail data about the environment have advanced rapidly; our ability to use this data for understanding the monitored settings for decision-making has not. Visual analytics, creating suitable tools and interfaces that combine computational powers with the human's capabilities for visual sense making, is a promising approach. Geosensor networks monitor a range of different complex environmental settings, collecting heterogeneous data at different spatial and temporal scales. Similarly domain experts with specific preferences and requirements use the collected data. Additionally, long-term monitoring networks may aim to increase sensor node longevity by minimizing storage and communication load. Based on these aspects, four key challenges for the extraction of knowledge about environmental objects and events from geosensor data are identified: dynamics and uncertainty of the continuous stream of recorded data; different scales in data collection but also data analysis at a range of aggregation levels; decentralized data processing and storage; and evaluation of the effectiveness, efficiency and completeness of implemented decentralized visual analytics approaches.

KEYWORDS: geosensor networks, environmental monitoring, decentralized computing, spatiotemporal data mining, geovisualization

Introduction

Recent technological advances in miniaturization of electronics and wireless communication technology are vastly improving our ability to capture real-time and high-detail data about the environment. An increasing range of environmental applications is adopting new sensing technologies for in-situ monitoring purposes. In particular, wireless geosensor networks (GSN) are arguably leading a "revolution" in environmental sciences (Hart & Martinez 2006). The new sensing technologies, combined with increasing needs to understand the pressures on our environment, are leading to another step change in the amount and complexity of data that are being generated. These new real-time data sources are changing the way environments are monitored to detect impacts across the spectrum of natural and built environments, whether monitoring changes to native or agricultural vegetation, to tracking mobile people in an urban transportation network, or moving fish in a sensitive river habitat.

However, advances in data capture have not been matched by advances in our ability to extract useful knowledge about environmental changes from these new data sources. That "we are drowning in information but starved for knowledge" is no less true today, two decades after this adage was first coined (Naisbitt 1982). Making smart use of the collected data is imperative to improve understanding of the monitored environments, to support effective decision-making, and thus to justify the investments in environmental sensing and monitoring. Visual analytics, the combination of human and computational powers in suitable tools and interfaces, to "detect the expected and discover the unexpected" (Keim et al. 2010) is a promising approach for improving sense-making.

This article explores examples of different environmental monitoring settings, the characteristics of the employed (wireless) geosensor networks, and the types of data collected through them. The specific characteristics of those settings, networks, and data provide a specific focus for the implementation of visual analytics approaches. Based on this, four key challenges in supporting the identification of meaningful patterns in environmental data from geosensor networks are identified.

Environmental monitoring settings

Rehabilitating native fish populations

In Australia, and indeed in many environments worldwide, trees and branches that fall into rivers provide important structural habitat for fishes. Unfortunately, over the past two centuries, many of these habitats were removed (desnagged), to allow easier navigation and faster delivery of water for irrigation. This has led to a significant reduction in native fish communities as many native fish use woody environments as a primary habitat. One current project that addresses this loss of habitats is being undertaken on the Murray River, in South Eastern Australia. The project is 'resnagging' some areas of the Murray River (reintroducing dead wood, Figure 1) to increase native fish populations. A data collection framework has been implemented to confirm that restoring woody habitats does not just redistribute the existing population but results in more fish. The most robust way to measure a potential increase in fish numbers is to estimate the population growth rate (population growth = birth – deaths + immigrants – emigrants) (Lyon et al. 2010).

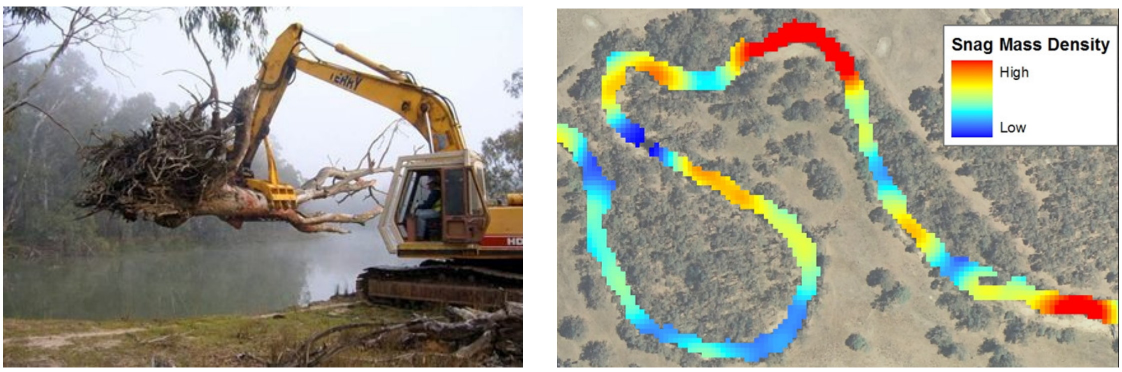

Figure 1: left) Resnagging Murray River, Australia;
right) Snag mass density in different river sections after resnagging

Data on immigrants and emigrants is being collected using radio-tagged fish. 18 logging towers record the movements of the tagged fish between different river zones bordered by them (Figure 2). The towers are equipped with directional antennas and are able to detect when a tagged fish moves from one zone to another by passing one of the logging towers. Thus, the collected fish movement data is location-based as opposed to the recording of time- or change-based trajectory data, which is more common in object tracking (Andrienko et al. 2011). Four of the monitored river zones are priority resnagging areas (colored zones in Figure 2). This allows for comparison of fish movement between unchanged desnagged and resnagged river zones. The spatial extension of the collected data is normally constrained to the course of the river. However, during times of flood, fish may also move into adjacent flood plains.

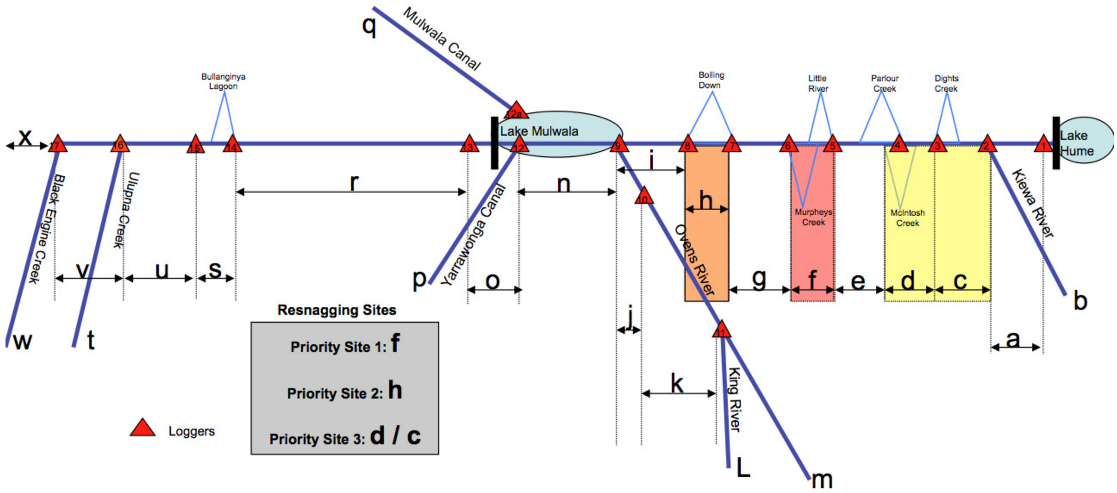

Figure 2: Logger tower schematic of the resnagging programm in Murray River; colored zones f, h, d and c mark priority resnagging sites (Lyon et al. 2010)

Environmental effects of conservation management

The Victorian Government's EcoTender program aims to provide environmental improvements by allowing private landholders to compete for contracts. These contracts enable landholders to receive funding to manage their land and water resources in accordance to the program's goals (Eigenraam et al. 2005). One of the challenges is the monitoring of the EcoTender sites to collect information about the progress and impact of the initiative. The landowners report annually the implementation and progress of their plan by detailed descriptions of actions taken and a series of photographs (DSE 2012). In order to improve this mainly manual process, and its limitations in regard to the detailed recording of changes in the environment, two sites were chosen as test sites for deploying wireless sensor nodes with different sensor capabilities.

The data were collected employing a geosensor network including iButton and iMote nodes (Figure 3). They measured and recorded temperature in °C, humidity as %, and light values in lux. The sensors also kept timestamps for each measurement. Each of the two sites was visited twice in March and June 2010 with the sensors recording data every five minutes for about 6-8 days depending on duration of battery life. Additionally, the approximate location of each node in space was recorded on a map.

Figure 3: Sensor network nodes iButton (left) and iMotes (middle);
part of the deployment map of site 2 showing approximate node locations (right)

Environmental conditions on the Great Barrier Reef

The Australian Institute of Marine Science (AIMS) needs to collect environmental data to understand the complex environmental dynamics of marine systems such as the Great Barrier Reef and subsequently to effectively manage anthropogenic stresses (Kininmonth et al. 2004). While such extensive structures cannot be monitored in their completeness it is critical that the strategic and opportunistic collection of data covers a range of spatial and temporal scales and permit answering specific research questions. One of the key questions is how various environmental factors impact on coral reefs. For example, increases in sea temperature are highly stressful to corals and result in coral reef bleaching (Berkelmans et al. 2004).

A number of autonomous weather stations measure air temperature and water temperature in multiple depths, salinity, wind speed, wind direction, light, and oxygen at different reefs in the Great Barrier Reef in North Queensland (Kininmonth et al. 2004). The data is quality checked and communicated directly, or via other weather stations when direct communication is not possible, to the central data server for storage and further analysis. If communication is not possible the sensors can store the information for several days during which the weather stations can be accessed and the data downloaded directly. The collection of information in different sea depths adds another dimension to data analysis. Understanding and analyzing data in three spatial and a temporal dimension challenges both visual and computational analysis methods.

Traffic monitoring and guidance

Transportation is understood to contribute significantly to environmental pollution, and waste of energy, time, and other resources. Technologies to capture data about traffic in urban settings have advanced and are now an integral part of central decision-making (e.g., fleet management), infrastructure-based decision-making (e.g., local traffic light management), or individual decision making (e.g., car navigation services accessing real-time traffic data, or safety-focused applications of vehicle-to-vehicle communication). The visualization of such real-time traffic data and its consumption in individual decision-making has not been well studied, however.

Traffic management centers all over the world can show on large screens the current traffic situation on a city's transport networks. Some services, such as the traffic mashup on Google Maps (Figure 4), provide similar information to the public for their individual decision-making. This data can be collected in various ways. For example, inductive loop counters register the number of all vehicles passing by, and these data are collected by local traffic authorities. Traffic cameras can form an alternative source. Mobile phone operators can monitor the electronic signals that are exchanged between mobile phones and the base stations that serve them, creating a real-time picture of where the phones are and how fast they are moving. Broken down to average speeds this data is anonymous and can be shared with information service partners. And finally, tracking vehicles of particular fleets, for example, taxis or courier services can serve as sampling of the traffic flow and produce similar data.

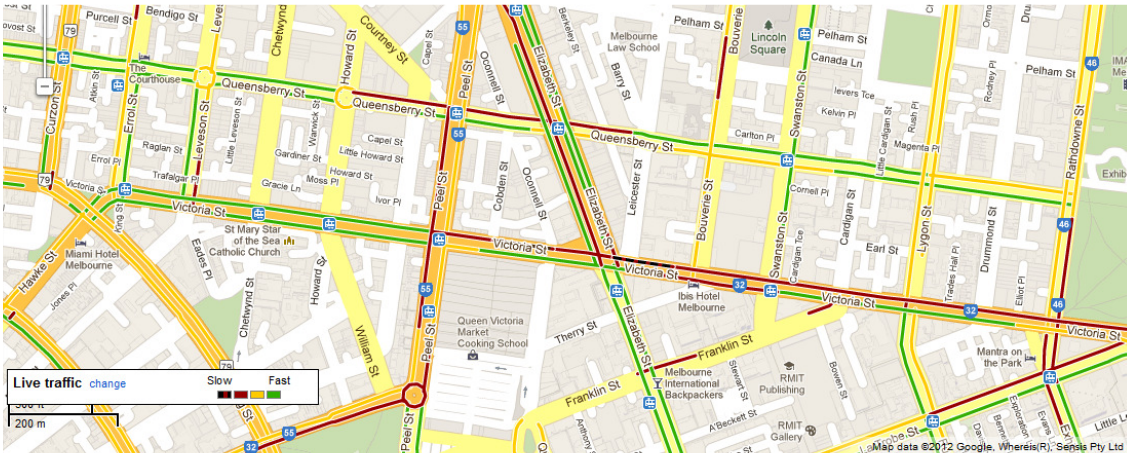

Figure 4: Part of a Google Maps® live traffic map: color-coded is the vehicle density (alternatively, depending on the environmental sensors, the average vehicle speed) along street segments.

A closer look at the communication by visual means raises doubts about the usability of this data. Car drivers recognizing that a segment ahead along their route has heavy traffic can draw unintended or at least sub-optimal conclusions. They cannot recognize whether the congested segment will still be congested when they will arrive at that segment; they cannot recognize whether the presented information to the public will guide many other drivers into their alternative routes; and they cannot recognize whether their route, even if congested, is no longer their optimal route. Furthermore, the use of colors has a psychological effect that may not be supported by the actual impact of the traffic situation on traveling along these streets.

Wireless geosensor networks and decentralized computing

The above example applications of sensor networks (summarized in table 1) store the data in the sensor nodes where it is collected for later download or relay the data to a central storage. While this allows processing of the data in a single location, it can be quite restrictive in terms of network deployment, as the nodes need either to be accessible or to possess enough energy and communication strength to send the data. We can think of a number of settings where those restrictions prohibit a sensible deployment of sensor networks. For example, in settings where sensors have to be very small and thus need to rely on limited energy resources but still should operate for as long as possible. In another exemplary setting, the sensors may be distributed over a large area or are collecting large amounts of data in short time intervals so that communicating all the data to a central server is impractical or even impossible. In such cases we may gain efficiency and longevity of the monitoring network through decentralized computing (Duckham 2012). In decentralized networks each node processes its own data and/or communicates with its immediate neighbors only. This reduces the load on network communication and, thus, energy supply (e.g. Chatterjea et al. 2006), but also means that the collected data can never be accessed as a whole. However, suitable decentralized algorithms allow achieving similar data processing results or getting answers to specific queries as would be possible when accessing and processing the whole data set (Duckham 2012).

Table 1: Summary of the case study characteristics.

Case study	*Organisation*	*Data collection*	*Scales*	*Data management*
Fish habitat monitoring	Arthur Rylah Institute	Logging towers recording passing of radio-tagged fish	18 towers along ~200km of Murray River, since 2006	Stored in logging towers, analyzed centrally
Conservation management	AmSI group, University of Melbourne	Sensor nodes recording temperature, humidity and light	Two sites, each ~1km^2, each monitored twice for 6-8 days in 2010 at 5min intervals	Stored in sensor nodes, analyzed centrally
Great Barrier Reef monitoring	Australian Institute of Marine Science	Weather stations and buoys recording, e.g., temperature, salinity, or wind speed	Various scales from spanning all reefs down to single corals	Relayed to central storage or stored locally, some decentralized data processing
Traffic monitoring	Several, e.g. local traffic authorities	E.g., inductive loop counters, traffic cameras, mobile phone information, and fleet information	Various	Generally centralized data storage and analysis

Smart data usage

The presented examples of networks monitoring natural and built environments show the diversity of goals and data collected. Based on those examples the following sections define the 'typical' data analyst, summarize the characteristics of the different data sets and tasks, and use these to focus the discussion of visual analytics methods for gaining knowledge from the collected data.

Data analysts

Usage and understanding of collected environmental data is largely dependent on expert users, like scientists, engineers, and resource managers, with existing domain knowledge and specific research questions. It is they who need to understand and to judge the significance of complex processes and interrelated events of an environmental setting that are potentially discernible from patterns, structures, or outliers in the collected data. It is they who are motivated by wanting to understand and to gain significant insight into the data. There is a large amount of evidence that suitable visualizations, especially when paired with appropriate interaction, can support such explorative tasks in large data sets (e.g., Andrienko & Andrienko 2010; Lam et al. 2011; Ware 2008; Wood et al. 2007). Tukey (1977) defined the concept of exploratory data analysis, which is more about exploring the data and generating hypotheses than answering questions or confirming hypotheses. Those concepts were taken up and expanded for the visual analysis of spatial and temporal data (e.g., Andrienko & Andrienko 2006). From our experience some users, especially engineers, often also want numerical answers and statistics, for example, event probabilities or confidence intervals. Those users are often less likely to sift through data for hours and employ a range of different visualizations to detect patterns in the data. Perer & Shneiderman (2008) have proposed a systematic but flexible guiding process for domain experts doing exploratory data analysis that may be adaptable to suit different expert users' requirements. This may also include a combination of statistics and visualizations for exploratory tasks (Perer & Shneiderman 2009). A simple implementation may visually encode data according to calculated values, for example, coloring values above the mean value in red. A combination of statistics and visualizations was also successfully employed to assess the quality of data or more specifically to find, for example, errors, duplicates or extreme values (Kandel et al. 2012). Additionally, there often exists a knowledge gap between visualization researchers and domain experts (Wijk 2006) and both parties need to work on closing it through common understanding of the goals and context to achieve useful visualizations.

Another important aspect of using visualizations regards the 'selling' of research findings. Researchers and analysts need to find ways to convey processes and patterns to the general public or a specific interest group, such as the Murray River's recreational anglers. This is no constraint to the design of explorative visualizations or interfaces for the domain experts as it could include the same but also completely different methods or visualizations. Additionally, it should not be neglected that most audiences also have domain specific knowledge. People may be interested in the topic at hand and be willing to spend some time analyzing data, and thus could make a valuable contribution to the process of data exploration and gaining understanding (employing the principles of crowdsourcing, e.g., Howe 2009).

Data and tasks

The spatiotemporal data collected by sensor networks in environmental monitoring settings shows some specific characteristics making it especially complex. Such data is typically: 1. highly detailed, at fine spatial and temporal granularity but also spatially and temporally auto-correlated; 2. highly dynamic, constantly changing with real-time environmental conditions; 3. heterogeneous, comprising data about a range of environmental variables, from water turbidity to gas concentrations; and 4. uncertain, using large numbers of low-cost, low-precision and accuracy sensors. Further, as a direct consequence of 1–3, the data also are highly voluminous. Additionally, if the data are collected and processed in a decentralized network we are constrained in the amount of data within a network that is accessible at a given time, space, or for a given query.

Often data collection methods are designed and implemented with specific interests and research questions in mind. Talking to domain experts they state that the collected data normally allows them to achieve those specific goals and answering their research questions. However, experts also mention a feeling that the data could tell or explain a lot more if they knew what questions to ask or what to look for. Other studies with domain experts have reported similar notions of there potentially being more information in the data than what can be detected by evaluating specific hypotheses (Saraiya et al. 2006; Bleisch 2011). Purpose-directed data collection has the advantage of answering current research questions. However, it may make combination of data with other data sets more difficult, even though such combination may allow the analysis of the data in ways and in relation to different environmental variables that were not foreseeable at the time of data collection. Exploration of network data sets should lead to a better understanding of the type or volume of data needed for efficient and effective environmental monitoring. Such knowledge will help in improving or designing current and future data collection networks.

A goal of visual data exploration is gaining insight (North 2006). It includes the analysis of the data sets from different perspectives and the visualization of them using different representations. For example, the fish data could be viewed as different fish changing river zones at recorded times or it could be the time stamped series of different fish swimming past a specific logger. For the visualizations we could choose to focus on the time series of moving fish, could use a spatial layout of fish movements or abstract the movement to a linear arrangement of zones that different fish move in and out of. Each representation may yield different insights and multiple interconnected views would allow harvesting the combined strengths (Roberts 2007). While the concept of gaining insights is useful it also makes it more difficult to evaluate the effectiveness of the visualizations as we may not previously know what we are looking for in the data (Saraiya et al. 2006). However, looking for ‘meaningful’ patterns implies that domain experts are able to make judgments in this regard.

Methods supporting smart data usage

The issue of extracting useful knowledge from complex data sources is a long-standing problem in the information sciences. Visual analytics approaches allow the combination of efficient spatiotemporal data mining algorithms for identifying candidate objects and events with interactive visualization to assist domain experts in selecting meaningful objects and events from amongst these candidates. These two perspectives can additionally be combined through linked views. In one view, users could explore complex environmental data sets intensionally, for example, by applying and parameterizing spatiotemporal data mining filters. In the second view, users could explore the data sets extensionally, for example, by selecting meaningful objects or events from the data set. A special focus lies on the user, data, and task characteristics as discussed above, which are to some degree specific to the applications and especially to decentralized networks. This tight focus, including explicitly targeting expert users, allows the adoption of a hybrid methodology that blends the key strengths of established approaches in spatial data mining (e.g., Miller & Han 2009) and visualization (e.g., Ware 2008). Spatial data mining allows for rigorous and objective computational evaluation; visualization provides effective mechanisms for human interaction and generating meaning. Additionally, it is important to evaluate the effectiveness and efficiency of those combined data analysis approaches. New ways for visualizing and analyzing data are regularly proposed but often with very little or no evaluation of their effectiveness (e.g. the proposed framework for visualization and exploration of events in sensor networks, Beard et al. 2008).

The research we are currently conducting implements and evaluates visual analytics approaches for data from a range of monitored environments, which store their data mostly centrally (cf. table 1). However, a specific focus lies on how those visual analytics approaches can be adapted to be suitable for data collected with low cost wireless geosensor networks which require decentralized data storage and processing to reduce network load. As described above, this may mean dealing with incomplete or vague information about the location of the sensor nodes, such as node connectivity rather than coordinates, time lags, as nodes are not perfectly synchronized, or only partial access to the data. Any node could be chosen to tap into the network data and ask specific queries such as what were the highest temperature recordings in the selected area over the last three days. Three days is a short period of time. We may however, also be interested in long term monitoring data. One aspect of our research is thus concerned with defining what information needs to be processed and/or kept within a network or specific sensor nodes so that different queries can be effectively answered while not placing an unduly high storage and communication load on the network. This could mean storing different average values, calculating gradient information between nodes or keeping track of data peaks and pits over time. Continuous processing and analysis of the data locally or regionally within a network should be able to remove noise and outliers, detect patterns and also send out warnings when extraordinary events are detected. For centralized analysis of spatiotemporal data it is known that meaning can be revealed at several scales (e.g., Keim et al. 2010) and thus data may need aggregation at different levels. The concepts for visual analysis at different scales seem to match well with the concepts of decentralized computing and storage in sensor networks. However, testing will be needed to ensure that key data are retained and valuable insight can be generated similar to that of a centralized data analysis approach even though single nodes or local groups of nodes decide about storing or discarding data.

Challenges

Technological developments are supporting the deployment of wireless sensor networks in an increasing variety of environmental monitoring settings. Enormous amounts of high-detail, dynamic, heterogeneous, and uncertain data are collected. But how can we understand the complex environments monitored and supporting decision-making? Based on the data characteristics, the discussions with domain experts, and the focus on decentralized data storage and processing for long-term environmental monitoring the following successive four key challenges are identified:

- Dynamics and uncertainty: The potentially moving sensor nodes record variations in the monitored environmental factors. The data is collected as a continuous stream at potentially varying time intervals containing evolving information. Geographic location may be imprecise or only implicitly available through network connectivity.

- Scale: While the data may be collected at different scales it may also reveal information at different levels of aggregation. Additionally, users may be interested in continuous data evaluation; may occasionally request specific, for example, spatially or temporally limited data; or are event-based prompted for data analysis.

- Network load: Decentralized processing and decision-making is important to reduce storage and communication load. Different analysis scales or spatiotemporal autocorrelation could be used as input for processing and for the decision about what data to store (e.g., Chatterjea et al. 2006).

- Evaluation: Evaluating the effectiveness and efficiency of visual analytics approaches is one important aspect. Additionally, it is essential to evaluate if reduced data storage and communication in the network, and thus not having access to the complete data set over space and/or time, leads to the same or similar data analysis results, as would a centralized approach.

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