Handbook of Research on Developments and Trends in Wireless Sensor Networks:
From Principle to Practice

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Section 4
Practices and Applications

Chapter 16
Visualizations of Wireless Sensor Network Data

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ABSTRACT

Wireless sensor networks can provide large amounts of data that, when combined with pre-processing and data analysis processes, can generate large amounts of data that may be difficult to present in visual forms. Often, understanding of the data and how it spatially and temporally changes as well as the patterns suggested by the data are of interest to human viewers. This chapter considers the issues involved in the visual presentations of such data and includes an analysis of data set sizes generated by wireless sensor networks and a survey of existing wireless sensor network visualization systems. A novel model is presented that can include not only the raw data but also derived data indicating certain patterns that the raw data may indicate. The model is informally presented and a simulation-based example illustrates its use and potential.

INTRODUCTION

Wireless Sensor Networks are quickly realizing a potential to support large and ultra-large scale data sensor, gathering and processing applications. Applications suitable for such wireless sensor networks include ubiquitous and quickly deployable systems that can meet the anytime and anywhere demands for quickly obtaining information about the environment, processing that information and then presenting that information to human communities to facilitate better understanding about the environment. The latter includes the visualization of the sensor information and is the main focus of this chapter.

There are many types of user communities that may be interested in the information obtained via sensor networks. Very broadly, these would include scientists, policy and decision makers, educators and general public interests. The first two types of

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communities are often involved in modeling and seek to understand the sensor obtained information as observations in the context of these underlying models; or, as in the case of the policy and decision makers, base professional decisions upon this understanding. Educators are primarily interested in facilitating the learning process and may use visualizations in two ways, either by considering the sensor acquired information singularly, or as combined with the underlying models. General public interests however would often be satisfied by merely the sensor acquired information. The visualization model described here incorporates both of these visualization levels and therefore suggests its wide-scope application potential.

There are many issues involved in the visual presentation of wireless sensor network acquired information to broad audiences. Some of data related issues include: large and ultra-large scale deployments, high frequency data acquisition rates, and, multiple imagery and multimedia streams. The presentation of information will also depend upon the needs of the user communities and in particular the selection of the information level appropriate for those needs. In particular, the decision makers may require presentations to afford sufficient depth of understanding in time-critical applications. Since the latter imposes additional requirements, the focus of this chapter emphasizes the visualization of wireless sensor network information for presentation to decision makers to facilitate understanding leading to effective decisions in time-critical situations.

The objectives of this chapter are three-fold. Firstly, to discuss issues about the potential large data set sizes generated by wireless sensor network. Secondly, to survey existing wireless sensor network visualization systems. And, thirdly, to present a new visualization model that can accommodate large data set sizes and address the limitations of existing visualization systems.

BACKGROUND

The primary purpose of sensor networks is to acquire information about some environment. Sensor data is obtained both spatially and temporally, and for purposes of this chapter, is assumed to be transmitted to a computational base station for pre-processing and visual displaying. The first part of this section discusses the significant large data set sizes that wireless sensor networks impose upon visualization systems based upon a simple analysis. The second part discusses several wireless sensor applications in context of current day realistic data set sizes. And the third part discusses several existing sensor visualization systems.

Characteristics and Properties

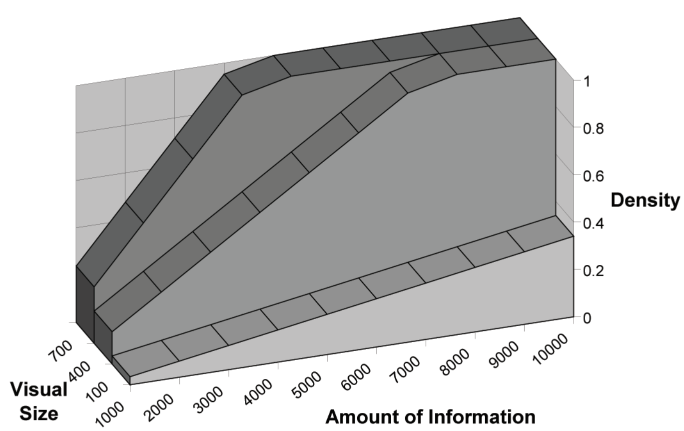
The ideal maximum amount of information available for a visualization is limited by the sensor communication bandwidth. Two communication technologies can be used. Radio Frequency based systems have bandwidths in the 40 kbps and 250 kbps ranges (Polastre, 2004), although, newer systems may be capable of somewhat higher rates. Free space optical based technology is newly emerging and can support data rates in the order of 10 gbps or higher (see d'Auriol et al., (2009) for further discussion). The kilo bits per second range is sufficient to support typical environmental data sensing such as acceleration, temperature or humidity; but not high definition imagery nor video; whereas, the giga bits per second range can support both. Assuming an eight-bit short word representation for environmental type data; then, a 40 kpbs data rate can deliver 5120 values per second, a 250 kpbs data rate can deliver 32,000 values per second and a 10 gbps data rate can deliver over 1.3 billion values per second. And, assuming a 1280 by 720 pixel, 24-bit color image (without compression); then, a 10 gbps data rate can deliver 485 images per second.

It is unlikely that the ideal maximums truly represent the realistic maximum information available for visualizations. In general, actual data transmission rates depend upon many other factors including sensor sampling rates, power utilization requirements, application requirements, and communication traffic properties; all of which could reduce the amount of information available to visualizations. There are additionally other operations such as data aggregation and data re-sampling (e.g. for downsizing) which could further reduce the amount of information. However, at the same time, derived information obtained from processing the sensor acquired or 'raw' data can be combined with the sensor data thus increasing the amount of information available to visualizations. In general, the amount of data used in a visualization depends upon these and other factors so as to support the extent of the human viewers' requirements and needs. Let us consider an available information modification factor (for brevity, this will be shortened to the term 'modifier' in the rest of this chapter) as a percentage of the ideal maximums; for realistic systems, the modifier will likely be quite low.

Visualization metrics define various measurable aspects of a visualization. Loosely, *visual density* can be considered to be a measure of how much data is displayed in a single visualization. At the extremes, the density is minimal for a 'blank' visual and is maximal if the information is encoded and presented as a single pixel. Usually, a single information item in a visualization requires many pixels for representation. Additionally, since sensor networks have distributed nodes, it is likely that the visualization would consist of multiple sensor nodes placed on the screen thereby further reducing the screen area available per sensor node.

The following analysis assumes a 1400 by 1050 color pixel output device. A standard character size of 12 by 8 pixels suggests a small but sufficiently recognizable visual primitive. Assuming one data value is mapped to one visual primitive and without regard for specific screen coordinate placements, then the visual density can be calculated given the amount of information obtained from the sensor network. Figure 1 illustrates this analysis: consider the three visual primitive sizes of 100, 400 and 700 pixels with increasing amounts of information from 1000 to 10,000 items at the modifier set to 0.5; then, for the 100 primitive size, there is enough space on the screen to represent this data, but when the primitive size quadruples, more screen space is devoted to each primitive and the density reaches one just before 8000 data values. This analysis, for

Figure 1. A visual density model: visual primitive sizes of 100, 400 and 700 for the number of information items from 1000 to 10,000 at a modifier set to 0.5



the 40 kbps data rate, with a primitive size of 100 and modifier set to 0.5 suggests that a maximum of five nodes can be viewed simultaneously; and with the modifier set to 0.1, suggests that 28 nodes can be so viewed.

Clearly, wireless sensor networks impose very demanding requirements upon visualizations. The simple analysis here indicates that low data rate and small scale sensor network deployments may be accommodated in visualizations; however, neither moderate nor large scale deployments can be. Visualization operations such as zooming, scrolling or panning could be used for moderate or large scale visualization applications. However, doing so places some additional requirements on providing navigational context information, and may depend upon the inherent relationships of the data itself (an obvious hierarchy here is the spatial placement of the sensor nodes where scrolling and panning would allow applications with many nodes to be represented and zooming would allow drilling down into the information content of a single node). Often, it may be very useful to isolate one or two parameters in a visualization thereby reducing the data requirements. There is in fact a large body of literature that is concerned with the visual presentation of large amounts of information and those techniques may also be of use as well. However, the implication of the afore analysis for large and ultra large wireless sensor network deployments (e.g. in the order of hundreds to tens of thousands of nodes interconnected by high bandwidth radio frequency or optical networks) is that a 'traditional' approach to visualization is problematic to providing a clearly understandable 'picture' of the information and its meaning to human viewers.

Analysis of Existing Deployments

This section briefly surveys several recent wireless sensor network applications in terms of the visualization presentation requirements. Several examples of real-world wireless sensor deployments suggest that past deployments had supported relatively low amounts of acquired data and that current deployments support more modest amounts of acquired data. Furthermore, several applications either directly indicate the need or benefit of incorporating underlying models for prediction purposes. For other applications, we believe that the incorporation of a model would provide enhanced benefit.

Mainwaring et al. (2004) discuss a wildlife habitat monitoring application (The Great Duck Island study). Their primary visualization needs include both the visual presentation of data as well as patterns indicated by this data. Thirty two sensors are deployed. The sensor data includes five essential scalars as well as desired additional scalar and vector data with data encoding sizes estimated between eight and 16 bits. The required sampling rates are significantly more modest than the maximums considered earlier and are based on a time scale of minutes and hours. Szudziejka et al. (2003) mentions that over one million sensor readings over a period of about five months were collected: "making it difficult to analyze the data".

Lédeczi et al. (2005) discuss an application for countersniper detection in urban combat zones. Their primary interest is the detection of sniper activity with associated geographical visualization. Fifty-six to 60 sensors are deployed. They indicate that sensor data can be comprised of seven scalars or vectors, although, in their work, they use only a subset of these parameters. Powerful local processing at the node is available. Two of these parameters are sampled up to approximately 100,000 samples per second at a 12 bit representation.

Stoianov et al. (2007) discuss an application for monitoring leaks and other anomalies in water pipelines. Much of their visualization needs are reflected in the detection and identification of anomalies in the water flow system. The data set includes several scalars and vectors. The required sampling rates vary depending on the specific data in the order of 1000 to 1500 samples every five minutes with a transmission capability of up to 600 samples per second.

More recent work indicate more demanding amounts of data: Chen and Chou (2008) describe a wireless system capable of supporting 50 to 100 streams at 500 samples per second; and, Barrenetxea et al. (2008) indicate on the order of megabytes of sensor acquired data available for visualizations.

Basha et al. (2008) describe an application methodology that includes connecting an underlying model useful for prediction with the raw data sensing. They also survey many other comparable systems and applications noting the absence of model predictive capabilities. Predictive models as well as augmented visualizations appear in Hull et al. (2006).

This brief survey illustrates the increasing size, availability, heterogeneity and demand of wireless sensor network acquired data as testbed applications give way to more broad 'real-world' deployed systems. For the most part, visual presentations of the information in these surveyed works rely on standard plots (for example, accelerometer data is mostly presented in two and three graph multiplots (see d'Auriol et al., (2008) for a detailed discussion), although, several applications incorporate map-based visualizations.

Past and present day wireless sensor network systems provide specific manageable data that is suitable for standard types of visualizations; however, the augmented demands for larger deployable systems in more complex application environments as indicated by the ideal communications maximums and the incorporation of underlying models studied here pose significant visualization manageability issues for even near-future deployments. Furthermore, an emerging theme noticed in some of the surveyed works includes generalizable approaches that reduce specific application, system or environment fine tuning of sensor and network parameters. Lastly, predictions such as in (p. 122, Wessner, 2006) suggest the continuing fast expansion in sensor-based systems.

Existing Visualizations

There are more than a few visualization environments, frameworks or systems that have been developed over the past years. (This observation is in stark contrast with the impression given by some of the recent publications in this area.) This is not surprising in that, as wireless sensor networks continue to transition to more complex real-world deployments, the complexity of the network as well as the sensing environment also continue to grow; thereby, driving a need for better visualization tools in order to deal with increased information content.

Visualizations of wireless sensor networks fall into three broad categories: visualizations of the network operational conditions (Network), visualizations of the sensed data (Sensed Data), and visualizations that combine network and sensed data (Hybrid). A survey of several existing environments, frameworks and systems using these categories for classification is given below. In some cases, the distinction between the Network and Hybrid categories is made based on the primary purpose and clearly dominate visualization capability of the particular system. In addition, visualization environments, frameworks and systems may be fixed, that is, the systems designer pre-selects the types of allowable visualizations, partially extendable, that is, the user may select from a wide-range of parameterizable options, or flexibly extendable, that is, the user may develop scripts as plug-ins.

Network

Visualizations aimed at the network operational conditions are often useful for two main reasons, first, to develop, test and debug sensor deployments, either in-situ or by simulation; and second, to monitor deployed network status and health..

Many of these systems also incorporate limited per node visualization of sensed data, often, associated with textual labels on a graph-based topology display or trend graphs of sensor data. Some systems are flexibly extendable, apparently providing support for additional visualizations, perhaps including visualizations of sensed data (however, at the time of this review, none of these systems provide much evidence of such application extension to sensed data).

The Emview tool, a part of the EmStar system (Girod et al., 2004), the ISEE sensor network monitoring environment (Ivester and Lim, 2006) isview tool, and the Sensor Network Analyzer (SNA) by DaintreeNetworks (Daintree, 2008) are examples of visualization systems that are primarily aimed at visualizing network operational information and provide very limited or no capability for sensed data visualization.

NetTopo is a recent simulator and visualizer for wireless sensor networks (Shu et al., 2008) that contains a testbed visualization module primarily providing network topology visualizations useful for analyzing network algorithms. The visualization display is subdivided into three regions: a display canvas, a node property display and a message display for use in logging and debugging. The authors indicate that visualizations of sensed data are also available via defining wrapper functions to obtain the sensed data, although it appears that some of this data is exported to other standard graphing applications.

TinyViz is part of the TinyOS mote simulator (TOSSIM) (Levis et al., 2003). This is a framework that manages the event and command interface to TOSSIM. Visualization is accomplished via plug-ins. A set of basic plug-ins are available and users may implement their own for specific purposes. The primary purpose of the available visualizations is aimed at network operational data which is displayed as a graph, although some basic plug-in are provided to display sensor values and contouring. Other plug-ins may be user defined allowing TinyViz to perhaps provide some additional visualizations of simulated sensed data.

Sensed Data

Whereas the general properties of wireless sensor networks beg a graph-based topology display, the domains of the environments sensed by sensor networks are specific. Broadly, general methods can be applied to the sensed data which share degrees of commonality amongst the data properties or specific methods can be applied which construct specific visualization models or systems for the specific data requirements.

Scattered data methods combined with Voronoi diagram abstractions are used by Szudziejka et al. (2003) to visualize temperature information obtained from the Great Duck Island study. Due to the properties of the sensed data, their visualizations are animation-based.

The augmented reality visual interface system proposed by Claros et al. (2007) combines visualizations of the sensed data with visualizations of the sensor physical environment. A visualization of the sensed data is firstly rendered and subsequently transformed into an image with graphical tags. This transformed data is used by the augmented reality application to position and display the visualization images onto a real-world scene; thereby, providing three dimensional environment scene contexts to the visualization.

WiseObserver (Castillo et al., 2008) provides a number of sensed data visualizations including evolution charts that plot graphs of sensed data over time; interpolation maps and evolution videos that provides spatial color mapping, contouring, etc. of selected data; and report generation that provides document along with text information. The windows graphical user interface also allows for multiple views to be displayed, thereby providing some comparative capability.

A more domain restricted sensed data visualizations include CarTel (Hull et al., 2006) which makes use of map-based visualizations to provide location information.

The sensed data visualization approach adopted by Fan et al. (2004) makes use of the GIS Geographic Resources Analysis Support System (GRASS) to provide map-based visualizations.

Hybrid

Hybrid systems provide visualizations of both network operational conditions and sensed data. In some cases, dual visualization approaches effectively provide for each independent of each other, in other cases, a combined visualization can be defined. The latter, whilst useful in understanding the conditions of the network in the context of the sensed data, may lead to increased confusion about understanding the implications of the sensed data in the context of the environment being monitored.

SpyGlass is a wireless sensor network visualizer (Buschmann et al., 2005) that provides information for use in sensor network debugging, evaluation and understanding of the software. Within this focus, sensed data can be visualized. The visualization component of SpyGlass consists of a graphical user interface that is subdivided into three regions: a display canvas, a sidebar for tree-structured textual information about the network and a message display for use in debugging. The canvas itself is three-layered and provides for background imaging, graph-based relational information between nodes displayed and node-based detail information about a node. Plug-ins can be defined for each of these layers thereby allowing specific visualizations to be defined as needed.

Octopus is a visualization and control tool for wireless sensor networks specifically designed for TinyOS 2.x together with a limited number of mote devices (Jurdak, 2008). Its graphical user interface incorporates two types of pre-defined visualizations: a network map for graph-based topology display, and a network chart for sensed data versus time curve plotting.

SNAMP provides a multi-view visualization framework for wireless sensor networks (Yang et al., 2006) that provides multiple views: topology, packets, measurement and sensing chart. The first three pertain to network operational data; the latter, to sensor data. The front-end visualizer allows the incorporation of user defined visualizations to the software.

In-Situ real-time visualization for difficult-to-work-in-environments is described in Selavo et al., 2006. The architecture for SeeMote device is presented, in particular, its LCD and LED buttons, and, visualizations of network operational data as well as sensed data are shown. Visualizations are limited due to the low-resource usage intention of the SeeMote device. New visualizations can be developed via scripting that are based on a limited number of visual outputs (e.g. lines and filled boxes, text, menus, and color).

The Mote-View (Crossbow, 2007) from crossbow Company is a commercial tool that incorporates visualization of the wireless sensor network (e.g. node status and network topology as well as the sensed data. For the latter, a set of pre-defined data level visualizations are provided via menu selection (data, charts, histogram, scatterplot and topology) together with a per node user selection dialog (which also displays some network status information). Mainly, these visualizations provide details about the sensed values per selected nodes. Additionally, there also are some limited comparison and statistical visualizations. Specifically: the 'data' visualization provides tabular detail of the sensed values, the 'chart' visualization provides for plotting per node (maximum 24 nodes) the data over time (maximum three sensor types, i.e. three graphs), the 'histogram' displays simple statistical distribution of single sensor (maximum 24 sensors) data, the 'scatterplot' displays two sensor readings against each other for a selected set of nodes, and the 'topology' provides for a node topology graph superimposed on a background, either a bit-map of the user's choice, or a colorized gradient of a selected sensor data. Related software, the Surge Network viewer also from the same company, provides similar although reported less visualization capability (see the discussion in (Buschmann et al., 2005)).

Summary

Almost all of the existing visualization systems and approaches surveyed above provide visualizations at the data visualization level; and leave the understanding and interpretation of that data to the viewers (although, the singular approach of Szudziejka et al. (2003), based on general scattered data methods, may have a broader scope).

Many of the visualization capabilities provide for visualizations of the wireless sensor network itself – for development, testing and debugging or for in-situ operational monitoring. This observation suggests two things: first, that, despite the intense research, development and deployment of wireless sensor networks, there continues to be real or perceived challenges to successful deployments that motive the continued development of these types of visualization systems, and second, that application deployments may not have yet reached sufficient deployment maturity necessary to motivate corresponding intense research efforts to provide effective visualizations of the sensed data. In many cases, visualizations of sensed data is well provided by systems that also well provide for network environment data visualizations.

The visualizations surveyed here are often informative for small sized networks; however, its usefulness for large-scale applications is less certain. In some cases, the graphical user interface provides standard panning or scrolling capabilities, however, with apparently little or no navigational context information available nor other more widely available virtual camera features (e.g. projection, zooming). As such, for the most part, these visualization systems represent typical, low-fidelity, and abstract visual representations of the information that suggest their unsuitability for large-scale applications. The singular approach of Claros et al. (2007), however, specifically addresses the fidelity and context issues.

In addition, some of the older or commercial software are either systems or vendor dependent making it difficult to adopt widely. Newer systems provide greater flexibility. In addition, intended future work on a number of these newer systems include further visualization developments (e.g. three dimensional visualization support).

MULTIPLE LEVEL VISUALIZATION

The Multiple Level Visualization (MLV) model is classified as a Hybrid model in terms of the categorical classification of the previous section since it defines a singular model that is equally applicable to either network operational data or sensed data. However, since the MLV model includes additional elements, its semantics are not found in any of the surveyed models, hence, a part of this model also lies outside of this classification. Although substantively different in approach, the work of Szudziejka et al. (2003) is closely related to the MLV model in that both aim at general methods widely applicable in different networks or for different applications; also, the work of Claros et al. (2007) is closely related in that both three dimensional environment scene context is provided. The MLV model is formally presented in (d'Auriol, 2009). However, various earlier aspects are presented in (d'Auriol, 2006; d'Auriol et al., 2006; d'Auriol et al., 2007). The presentation of the model here is semi-formal to allow for easier reading and understanding. The MLV model is based on the alternative approach of connecting an underlying model with the sensor acquired data. We suggest that various features of our model may be applicable to much of the afore mentioned surveyed work; and, by virtue of its alternative basis, may be able to partially address the large data size issues. Lastly, the idea that an underlying model supports the observations provided by wireless sensor networks has been previously mentioned (see for example, (Sect. 7.5, Zhao et al., 2004)), although, the afore mentioned survey does not indicate such incorporation into sensor network visualizations.

In general, the information obtained from a wireless sensor network has two fundamental properties: structure and value. Structure refers to the x, y, and z coordinates of the physical sensor placement, its GPS coordinates or some other placement location coordinates. Value refers to the measured or observed information obtained by the sensors. Values may either be defined in discrete or continuous space and have associated minimum, maximum and normal operating ranges, for example, temperatures inside of a living room or the voltage and frequency of power lines. These properties have often been noted elsewhere in the literature; see for example (Brodlie, 1992; Ware, 2004). In much of the visualization literature, structured information is referred to as data.

Sensor data is obtained from a single sensor at different times and hence it is an ordered set of values. Let $D^*_k=(D_1, D_2, \ldots)$ denote this ordered set for the kth sensor and where D_i denotes all of the sensor data at some ith time. Each sensor obtains a data vector consisting of structured and value components. Let $D=(d^s_o, d^s_1, \ldots, d^s_{m1-1}, d^v_0, d^v_1, \ldots, d^v_{m2-1})$ for m1 coordinates and m2 values and each d^v_i is defined on some interval representing the range of the sensed information. D^s denotes the structure subset while D^v denotes the value subset. A data level visualization is any visualization of D^*_k.

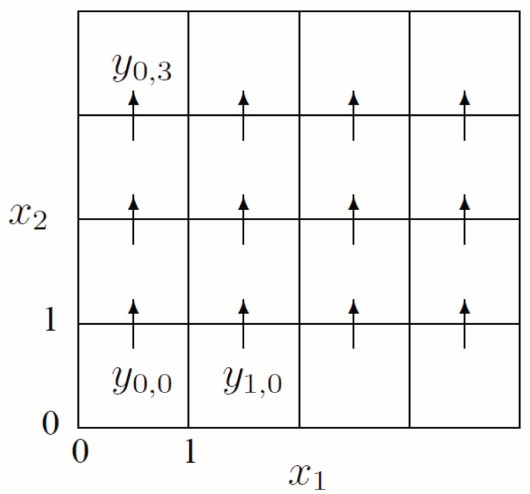
Data level visualizations are very commonly found in both the research and popular literature (see the previous section). By itself it can be very useful in facilitating understanding about spatial and temporal environment changes reflected by the sensor acquired data. However, the semantics of the environment comes from human understanding about the environment; in this sense the sensor acquired data are stand-alone entities without predefined semantics. Data level visualizations tend to be straightforward using well-known techniques such as coloring or contouring on a map (see the previous section).

However, in many situations and environments, there exists some underlying model that either may describe these spatial-temporal changes or predict such changes. Often, in science, an objective is the discovery of such models; in engineering, the design of systems based on such models. For policy and decision makers, the predictive capability of such models can be used as the basis for decisions. In some cases, an underlying model is either difficult to develop or is not known. Nevertheless, in all of these cases, an underlying model provides semantics for D^*_k. For many sensor network systems, the sensors are placed so as to provide observations about some underlying model.

A typical dynamic systems model determines a state space, often continuous, that represents the states of the variables in that system (see (Dorf, 1974)). This continuous state space can be discretized and thus represented by a specific type of finite state machine called an Orthogonal Organized Finite State Machine (OOFSM) (d'Auriol, 2006). Consider a one dimensional system: a collection of temperature sensors where one may discretize this system in sub-ranges say of ten degrees; or, frequency sensors of a power line where one may discretize in sub-ranges say of [58,60), [60,60] and (60,62] Hz. These discretized states can further represent nominal operative conditions, exceptional conditions or abnormal conditions of the system. In general, each state space variable represents an orthogonal parameter and hence very high dimensional OOFSMs can be defined; for example, even small power grid models may have dimensions of several hundred variables. In general, finite state machines have been used to model dynamic systems, see for example (Blouin, 2003; Cassandras & LaFortune, 1999; Jodogne, 2002; Marchand et al., 2000).

More formally, an OOFSM represents a lattice partitioned, and therefore a discretized, state space of a dynamic system and is defined by the tuple M=(Y, L, VY) (the notation is greatly simplified here, see (d'Auriol, 2009; d'Auriol, 2006) for a

Figure 2. Illustration of a two dimensional OOFSM with a uniform partitioning, 16 states and two uniform regions (source: modified from d'Auriol, 2006)



detailed mathematical presentation). The lattice partitioning L applied to an n dimension state space leads to a set of discretized states Y and in general defines a set of partition boundaries of the state space. A trajectory of the state space is the evolution of a set of state space parameters from one state to another. In terms of the OOFSM, the evolution is noted as the state to state transition across a partition boundary. In general, there exists a set of possible trajectories, many of which will intersect the same boundary and effectively reduce to a single state to state transition; however, many others may intersect other partition boundaries thereby defining multiple possible state to state transitions. The region field set, VY, denotes the union of all of these state to state transitions across the OOFSM. And a uniform region field is a collection of states all which have the same region field (subsets of VY can be uniform). A formal proof of the OOFSM's representation of such a system's state space is given in (d'Auriol, 2009; d'Auriol, 2006). Figure 2 illustrates this for a two dimensional system of four discretized states in each dimension; here, there are two uniform region fields with the first being null (terminal states) associated with the `top row' and the second being `up-wards only' associated with the remaining states; the lower-case 'y's indicate specific states in Y. Diagonal transitions are disallowed; however, changing the resolution of the partitioning will often reduce or eliminate such transitions.

If a dynamic system is known, than the dimension and variables of the state space are known and L can be determined based upon computational or other requirement. The system also may provide predictions about how the states may evolve thus deriving VY. Sensor data represent observations about this system (if observable) at a particular point in space and time and either confirms the prediction of the model or does not. Specifically, sensor data determine specific states and changes between sensor data determine $VY_{s.}$ When VY_s = VY_s, then the sensor data confirms the model; however, when $VY_s \neq VY_s$, then the sensor data suggests some abnormal condition that may be outside of the model. In both cases, the semantics of the model extend, although by different degrees, to cover the situation or events records by the sensors.

However, for the case where there is no dynamic system or it is unknown, the sensor acquired data can still be used to determine the OOFSM. Specifically, let L either be applied to D^s or D^v. The former implies that the OOFSM's structure is based on the physical space of the sensors and that transitions through this space reflect relationships between the values provided by the sensors. The latter implies that the OOFSM's structure is based on the observable state space variables. In this case, the semantics is similar to that when an underlying model is known, albeit without the ability to compare with model predictions.

An extended example is now discussed. A grid of 5 by 5 by 5 temperature sensors is simulated for a particular room location. A known underlying model for the temperature distribution in this room is assumed and therefore the visualizations

Figure 3. Top view of temperature state space

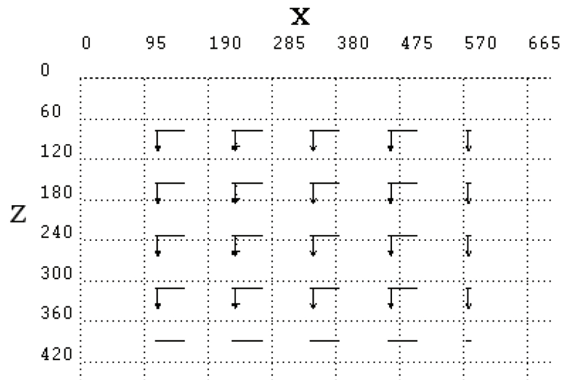
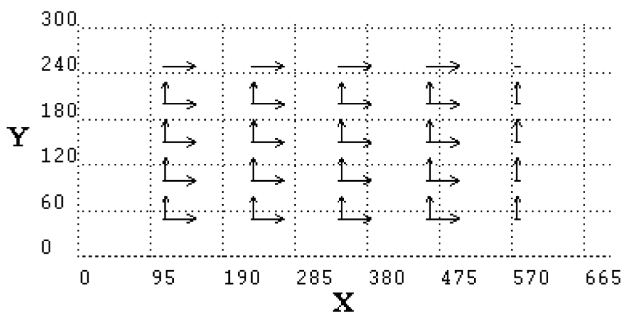


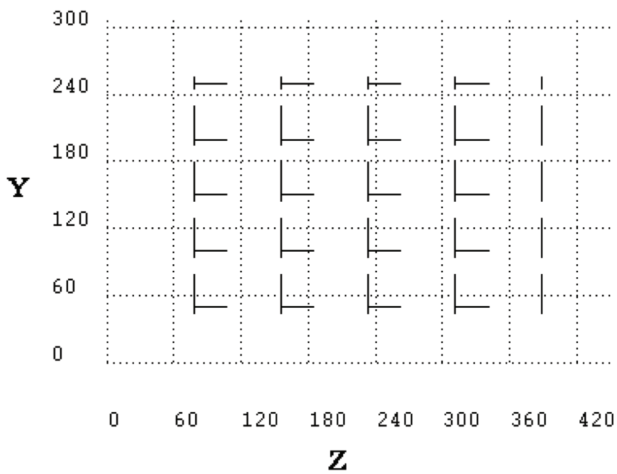
Figure 4. Front view of temperature state space



discussed seek to identify normal, unusual or abnormal environment conditions between the predictions of the model and the simulated sensor recorded values. The selected room location is part of the uLCRC (ubiquitous Lifecare Research Center) located at Kyung Hee University Global Campus in Korea. The uLCRC is a long-term academic, corporate and government consortium which aims at monitoring daily life of human behaviors and activities as well as providing proactively context-aware health related services via various types of sensors in an integrated environment. The uLRC consists of three rooms however, only the main office room is modeled in this simulation. The room contains a single air conditioning unit located in a corner and is modeled as a point source of cool air. There is also a single door, located at a different corner that provides an entrance from the hallway to the facility. In the simulation, the opening of the door assumes that warm air is introduced to the room. Figure 7 shows a cut-away of this room: camera images are texture mapped to rectangles representing the room's walls, the air conditioning unit is shown at the back-right of the room, the door, not shown, is located at the front-right of the room. A simple linear air current model is used in the simulation; for more realistic simulations, a standard thermal convention model could be used. The simulation determines the expected air temperatures at each coordinate of the temperature sensors.

Since the simulation includes a known model, the state space is three dimensional representing the x, y and z coordinates of the sensor locations (this would also be appropriate for the partitioning of the structured data components in the unknown

Figure 5. Side view of temperature state space



model case). An OOFSM is therefore determined based upon the partitioning of this physical space placing each sensor within a single state. The objective function $T_i > T_j$ for temperatures T_i and T_j obtained from two neighboring state-based sensors determines the state to state transitions (this function is derived from the underlying model's semantics, namely, about the temperature distributions, although, it would also be appropriate for the partitioning of the value data components in the unknown model case). Figures 3 – 6 show the top, front, side and three dimensional views of these OOFSM transitions as arrows (all visualizations are done in AVS/Express). In general, the color of each arrow represents the sensor acquired values (however, neither color nor grayness is included in these figures). Other than the edge states, the uniformness of the region is apparent. These visualizations show expected behaviors of the temperature system in the room.

Figure 7 shows the combined data and underlying model level visualizations for this simulation embedded in the three dimensional room scene. There are three elements of data level visualiza-

Figure 6. General view showing the three dimensional temperature state spaces

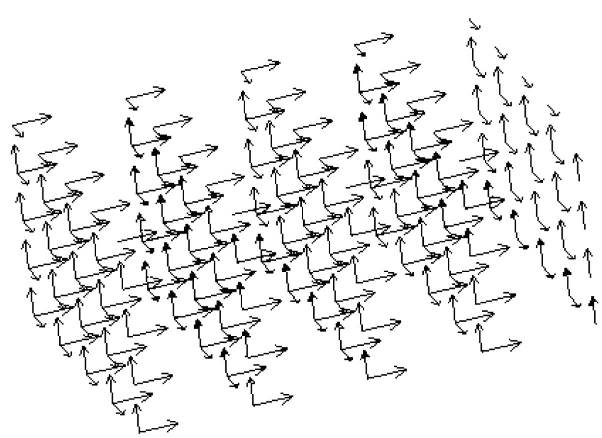
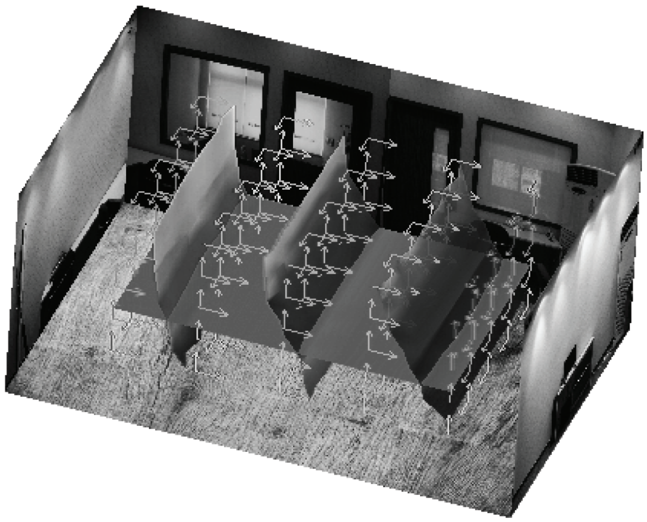


Figure 7. Combined data and model level visualizations



tion incorporated here: the colors of the arrows represent the temperature values, three isosurfaces together with the orthoslice show the temperature distribution throughout the room. Note that, by itself, the data level visualizations do not incorporate the semantics of the underlying model, that is, the precise possible trajectories of the temperature distribution are not evident. However, when combined with the underlying model visualizations of the state space, the semantics of warmer to cooler air transitions are indeed evident. Nevertheless, since the sensor observations confirm the model predictions, the additional semantics provided by the state to state transitions may not provide much in the way of additional advantage in understanding the temperature distribution.

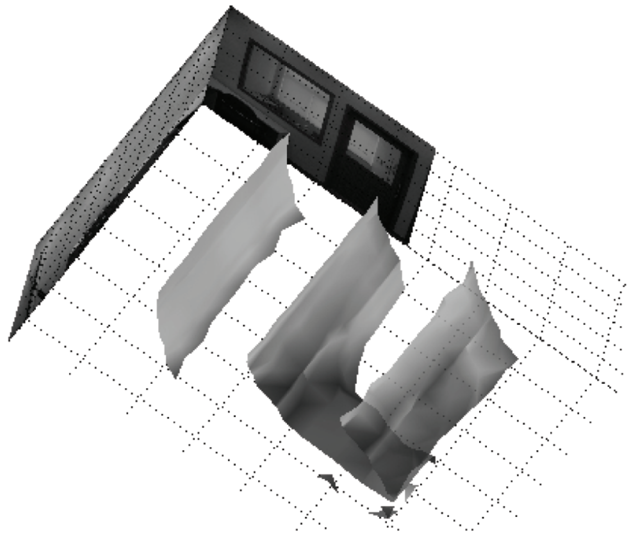
The next part of the simulation introduces a heat source as the external door is opened. Although a similar thermal convention model could be used to model this event; and a combined model could be developed to model the interaction of both events, in general, we may assume that some unpredictable event could cause a change in the state space observations which do not correspond with the predictions of the underlying model. Let us consider this assumption in the following discussion.

Figure 8 shows the data level visualization corresponding to the assumed abnormal condition of a heat source in the front-right of the room. Comparing with the previous figure, the isosurfaces are significantly changed in this part of the room. However, the visualization itself does not provide any clear indication of an abnormal condition. Indeed, it would be left to the human viewer to decide based upon experience and/or knowledge that the isosurface shape in this figure shows some abnormality.

Figure 9 shows the state space visualization corresponding with the underlying model. Note that the front-right state to state transitions form a clearly identifiable region that has different behavior from the rest of the figure. Both the regional localization and the regional behavior are evident from this type of visualization. In general, a rich visualization is potentially available when both visualization levels are included.

The previous section introduced a simple model based on visual density calculations to illustrate the size and scope of sensor acquired information. Here, this model is applied to determine how well the dual level model presented here may address this issue. First, since the data level visualizations rely upon the same set of visual

Figure 8. Data level visualization of abnormal conditions



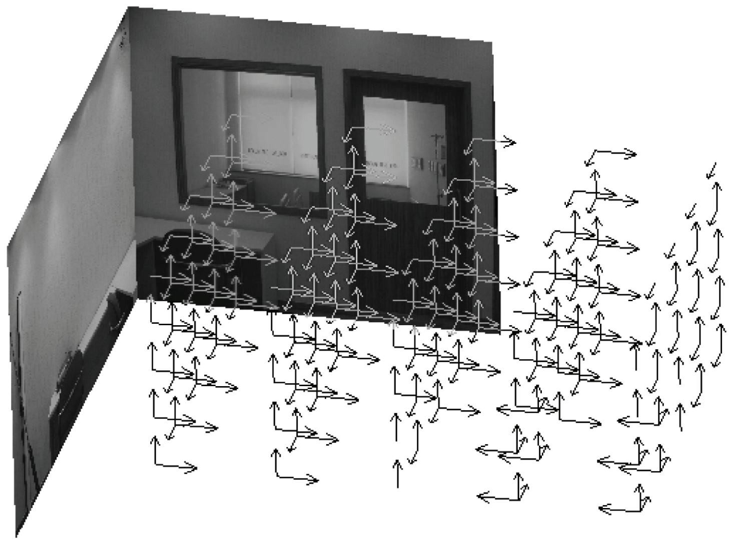
primitives as assumed previously, there may not be any savings without some further manipulation. Second, as visual primitives go, arrows take up very few pixels and may be closely aligned, that is, many more arrows could be utilized than the previous analysis would suggest. However, the incorporation of a large set of like arrows could increase the visual clutter in the visualization and thereby detract from the overall benefit provided by this model. In many cases, individual state behaviors are not of interest; rather, it is the region's size and behavior that is much more interesting. Although the presentation of the model in this chapter does not illustrate this, it is possible to compress uniform regions into a single 'super-state' like representation; of course, any data level visualizations would also require corresponding transformations. Doing so addresses the first issue in that less specific data points are used in the data level visualization and address the second as fewer arrows of the same orientation are incorporated into the figure. Zooming can be used to drill into specific regions.

There are two final comments about the potential application of this multilevel visualization model. First, the state space of the underlying model may be very large (almost certainly will be much greater than the three dimensions of this extended example). A subsequent model is needed in which to provide either state space reductions or state space navigation so that the high dimensional OOFSM can be explored. Such a model has been considered in (d'Auriol et al., 2006). Second, the state space of the underlying model may not overlap with the physical space of the sensor network environment, as was the case in the extended example. In general, the state space describes a model of a system that is embedded in the physical space; then, the overall parameter space could be combined and again, the model in (d'Auriol et al., 2006) may be used as well.

CONCLUSION

Visualizations of wireless sensor networks and data obtained from these networks are very important to both understanding the operational characteristics of the networks and the behavior and 'meaning' of the sensed data. A simple categorical-based classification is introduced in this chapter in order to distinguish visualization systems that are mainly intended for visualizations of network operational conditions from those that

Figure 9. Abnormal region of behavior



are mainly intended for visualizations of sensed data; and from those that provide for both. A number of visualization environments, frameworks and systems that have been proposed in the past years are classified accordingly. The survey reveals that many of the visualizations of network operational data are typical (i.e., graph-based, node-labeled, or chart-based) and low-fidelity; although some may be under development to provide higher quality visualizations. The survey also reveals that some of the visualizations aimed at sensed data are of higher quality.

Wireless sensor networks can also provide large amounts of data that when combined with pre-processing and data analysis processes can generate large amounts of data that may be difficult to present in visual forms. A simple analysis based upon the maximum amount of information that can be delivered from the sensor network together with a survey of several wireless sensor network applications suggest that near future sensor deployments could generate more information than can be accommodated by typical visualizations. The surveyed existing systems aimed at visualizations of network operational conditions are informative for small scale networks; many of which are scalable in terms of network size. However, as networks grow larger, many of the visualizations in these systems may not scale adequately due to issues such as context and navigation. Even those systems aimed at visualizations of sensed data may also have scalability issues. The generation of large amounts of data from wireless sensor networks continues to pose challenges.

This chapter introduces a novel model called the Multiple Level Visualization (MLV) model that is developed to address some of the aforementioned limitations and provide more advanced and higher-fidelity visual display. The MLV model combines visualizations of either the sensed data or network operational data with that of an underlying model that describes the semantics of the data. It is the inclusion of the underlying model that constitutes the unique direction of this model. An extended example illustrates the MLV model (although this example only covers visualizations of sensed data). An application of this model for large and ultra large scale sensor deployments that includes zooming, navigation and other visualization features and capabilities could provide a solution to address some of the issues inherent in the visualization of information from these types of sensor deployments.

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KEY TERMS AND DEFINITIONS

Data Level Visualization: Visualization aimed at displaying the values and patterns of the sensed data, may be combined with derived data visualizations, that is, visualizations of pre-processed sensed data.

Multiple Level Visualization (MLV) Model: New visualization model that combines data level and underlying model level visualizations so as to provide underlying model semantics coupled with standard data visualizations of the sensed environment.

Orthogonal Organized Finite State Machine (OOFSM): A special finite state machine abstraction used to represent the state-space transitions and state-space regions of behavior of the underlying model.

Underlying Model: Dynamic system model composed of state-space parameters either observable or not which provides semantics about the sensed environment; observable parameters are sensed by the wireless sensor network.

Underlying Model Level Visualization: Visualization aimed at displaying the state-space transitions and behavior described by the underlying model.

Visualization: Displaying information appropriately to facilitate human understanding leading to decision making about the sensed environment; usually, pictorial or graphical displays.

Wireless Sensor Networks: Networks of sensor nodes capable of acquiring sensed information about the environment and communicating that information via wireless data links to base stations.