Visualizing Sensor Data

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Abstract— As costs and size of microprozessors and sensors decrease, interest in using sensor networks for various applications of the most different kinds grows. According to this fact rises the need of exploring best ways of sensor deployement, data acquisition from a network as well as visualizing the sensed data. This paper deals with the last of this needs through the contemplation of sensors and their data delivery, of visualization criterions and the try to merge sensor data and visualization. Sensor networks can vary from very small to very big depending on the number of sensors included and the number of measurands, a sensor node is able to sense. Hence exists a wide range of different applications, sensor networks can be used at, creating an even wider range of possible visualizations. Besides the application the raw sensor data as well as position and time of a measurement are the main aspects when deciding on a visualization.

Index Terms—sensor data, visualization, sensor network, extraction, application

1 Introduction

Due to the technical progress of the last decades, which enables the production of small sized micro processors and sensors at a low cost, a new research area has developed, dealing with wireless sensor networks. These networks mostly consist of a large amount of tiny sensor nodes, which combine sensing, data processing and communicating components [5]. To ensure these three functions the nodes feature a number of sensors, a micro computer and a wireless communication device [8].
The general purpose of such a sensor network lies in its deployment in or very close to a phenomenon a user wants to observe. After a network is deployed the mere act of sensing includes the following three working steps. Step one is the measurement of a physical property by one of the sensors. The second step involves the micro computer which computes the data delivered from the sensor depending on the desired result. In a third step the computed data has to be transmitted from the sensor node to its destination, where it is often stored in a database. *Fig. 1* shows how data from sensor node A could get to the user.

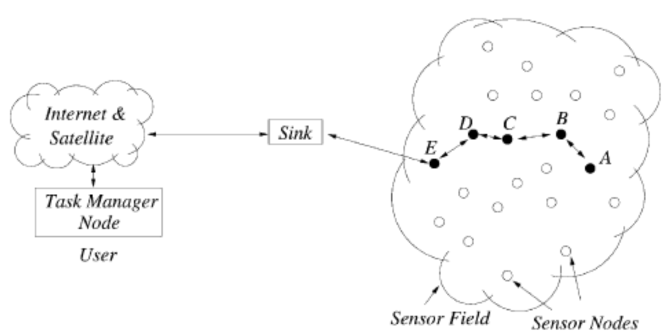

Fig. 1. Sensor nodes scattered in a sensor field [5].

After several hops inside the sensor field the sent information reaches a so-called sink, which communicates with a task manager node via internet or satellite. The sensor network itself is thereby a self-organizing network with a certain protocol stack used by the nodes and the sink.
After these three steps, which have been enquired rather widely, follows a fourth step, which is rather poorly explored, namely the visualization of the sensor data. Just seeing the raw data of a sensor network stored in a database mostly does not fulfill the needs of the users. So the data need to be analyzed and shown to the user in a way, where information can easily be gained from them. Which kind of information can be gathered from a sensor network, depends on the application area the network is used in.
Due to the enormous amount of different sensors (see 2.1) there is a wide range of such application areas for sensor networks. One of these areas are military applications. Sensor nodes are used here for reconnaissance of opposing forces and terrain or targeting. Environmental applications like forest fire detection or tracking of animals represent another interesting area. Even in medicine there can be gathered benefits by the use of sensors for example in monitoring a patients physiological data [5]. An overview of possible application areas is given in *Table 1* adopted from White [21].

Table 1. Fields of application for sensors [21]

Agriculture
Automotive
Civil engineering, construction
Distribution, commerce, finance
Domestic appliances
Energy, power
Environment, meteorology, security
Health, medicine
Information, telecommunications
Manufacturing
Marine
Military
Scientific measurement
Space
Transportation (excluding automotive)
Other (specify)

Only by knowing which kind of sensors are used in a network, which data these sensors deliver and which goal the user wants to reach by sensing a phenomenon, there can be chosen a meaningful visualization.
The remainder of this paper is organized as follows: Section 2 will contain a closer look at sensors and which data they produce. Section 3 provides an overview of what has to be taken into account when visualizing data. A discussion about the assignment of sensor data to a visualization taxonomy is found in Section 4. Section 5 contains the conclusion of the paper.

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2 SENSORS

As mentioned above sensor networks consist of a large amount of tiny sensor nodes. The following section therefor will deal with sensors by looking at several of their aspects. It will be shown different classifications of sensors, ways to gather data from sensors and the relevance of the position of a sensor and the time of its measurement. At the end of the section an existing sensor network will be introduced.

2.1 Different kinds of sensors

A sensor can be defined as "a device that receives a stimulus and responds with an electric signal ... [, whereby] stimulus is the quantity, property or condition, that is sensed" [11].

There exists an enormous variety of sensors, based on their measurands, which are shown in *Table 2*. All these physical properties can be recognized by sensing components. In a sensor node there are often found combinations of different sensors to explore a phenomenon not only by one aspect.

The classification of a sensor can be made simple or complex. An example of a simple classification would be to differentiate between active and passive sensors. A passive sensor responses directly to a physical stimulus without the need of an additional energy source by transforming the stimulus energy into an electric signal. An example here would be a photodiode. On the other hand active sensors are connected to an external power source, which is modulated to create the output signal. For example a thermistor has a certain resistance at certain temperatures. This means the temperature can be measured by detecting variations in the voltage across the thermistor [11].

Sensors can also be classified as absolute or relative, whereby the difference lies in the selected reference a measured value is related to. An absolute sensor would refer on an absolute physical scale, like for example the thermistor mentioned above to the absolut temperature scale of Kelvin, while the signal of a relative sensor has to be seen in perspective to a given value. For a relative-pressure sensor such a value might be the atmospheric pressure to build the baseline for the sensors measurements [11].

A complex classification of a sensor could be a description of all of its properties: Its measurand, its technological aspects (sensitivity, speed of response, ...), its detection means, its conversion phenomena, its materials and its application area. Examples for this classification are found in [21].

2.2 Sensor data

All the different kinds of sensors share the same purpose. They ought to respond to a physical property by converting it into an electric signal, which can be operated on to produce an output [11]. How this physical conversion is managed inside the sensor node is of no importance for our goal of visualization. The importance lies in the delivered data such as for example the momentary temperature at the sensors position.

Depending on the application there are different ways to gather data from the sensors. By having a look at the applications themselves, they can roughly be seperated into two parts: Analysis and event detection. In an analytical application the user wants to access data at a certain time, to watch the status of a phenomenon. For example when tracking an animal the user wants to know what is the animals momentary position. Or the user wants to trace a certain development by looking at fresh data and comparing them to older data. On the other hand sensors are used to detect events. An example here would be a motion sensor of an alarm mechanism that informs the system of an intruder.

So there are two main ways to gather data from sensors: on one side sending a query to a sensor, which answers it, or on the other side getting a message from the sensor itself. Wireless sensor networks mostly use the first method due to numerous constraints like for example the power costs of communication. There have been developed systems to simplyfy the creation and spreading of queries. One of these systems is TinyDB [16], which uses a SQL-like query language called TinySQL and works on sensor nodes using TinyOS [3] as operating system. The user can create simple 'SELECT ... FROM ... WHERE ...' queries and define a certain period in which the query shall be executed by a 'SAMPLE PERIOD' clause [7]. The query is spread over the network and nodes that accomplish the queries goal send back data to the user. If the user wants to collect data to observe a phenomenon over time, it is useful to store the measured data in a database. Otherwise the momentary results have to be shown to the user in an understandable way, as the query only creates a table full of measurements.

TinyDB also supports event detection: If a node shall react to a certain event, it must know what query to start at which event. That means that an 'ON EVENT ... SELECT ... FROM ... WHERE ...' definition must be found in the nodes code. On occurrence of the event a node or several nodes start sensing and send their measured data back to the user, which has to be informed by the system about the detection of the event [15].

2.3 Relevance of position and time

Beneath the data measured by sensors two other values have to be considered as important. On the one hand a user of a sensor network wants to know, where the sensor, that delivers the data, is to be found. On the other hand it is useful to know, when a sensor caught an event. According to Roemer and Mattern [18] there are different use classes of space and time in sensor networks. One of these use classes would be the interaction of an external user with the network. The user, which may be a human operator or a computer system, often defines special "regions of interest in spacetime such as 'only during the night' or 'the area south of ...'" [18] to accomplish a certain goal of an observation. Another use class is the interaction of the sensor network with the real world. As many distributed sensor nodes observe the same phenomenon, it is necessary to use data fusion to gain reliable information, whereby space and time are important components of data fusion. Also different instances of a physical phenomenon detected by a sensor network can only be distinguished by spatial or temporal aspects. These are only some reasons for the importance of position and time in sensor networks.

When looking at the position of a sensor node in a network, there can be distinguished two different kinds of deployement: A node can be installed in a fixed place or distributed arbitrarily in a wide area. The first method is rather suitable for smaller networks with only a few nodes, while a network of some hundred nodes can for example be spread by an airplane over a research area.

When installed in a fixed place, it is no problem to define the position of a node. The application collecting the sensor data can for example hold a table of all the sensors in the network, containing among others the nodes ID and its position. When a node delivers data, it includes its ID, so the application can check, where the node is positioned.

When distributed arbitrarily a node does at first not know its own position, but has to compute it. This can happen either by the nodes sensing components or by making use of the connectivity inside the network. Furthermore a node can on one side achieve its relative position inside the network or on the other side its absolut position in a global coordinate system. There are several different approaches for node positioning explained in [17]. An example for a node positioning system would be the Recursive Position Estimation, where 5 percent of the nodes are GPS-enabled and always know their exact position, while the other nodes gain their position by trilateration to such GPS-nodes or nodes, that already have computed their position [6].

Also time synchronization is important inside the network. Either the nodes are equipped with receivers for time infrastructure, which is not suitable for large networks with tiny sensor nodes due to energy, size or cost constraints, or the time synchronization has to be obtained in the same ways as the node positioning [6]. At this point there can be used a global or a local time scale, whereby the second one might be easier to handle.

In the cases of node positioning and time synchronization the nodes deliver their position and the timestamp of the measurement together with the sensed data to the user.

2.4 An existing sensor network

An example of an existing sensor network would be the collaboration of SensorWare Systems [2] with the Huntington Botanical Gardens in San Marino, California, since June 2000. In August 2001 there were deployed eleven so called Sensor Web pods, which are building a permanent wireless sensor network system for environmental monitoring. The system was extended to a 20-pod system in January 2003 and improved by a newer version of the pods in June 2003. *Fig. 2* is showing such a pod standing in the Huntington Botanical Gardens.

Fig. 2. Sensor Web pod in Huntington Botanical Garden [1].

These pods are equipped with a radio for communication with other pods, a microcontroller, a battery pack with solar panels, a special packaging to ensure weather resistance and a sensor suite. This suite contains different sensors to measure air temperature, air humidity, and light levels as well as soil temperature and soil moisture at two different depths. Additional measurements hold information about the pods health status like its battery status or its own temperature. Measurements take place every five minutes. The Sensor Web is not a typical wireless sensor network as it uses relatively big sized pods and omni- as well as bidirectional communication. This means a pod broadcasts its measurements to all other pods. Thereby a pod itself can gain information from four different types of data: Its own measurements, data from one or more other pods, commands of an external user or commands of another pod. This can for example help a pod to check its own measurements by comparing them to those of surrounding pods. One selected pod thereby acts as portal pod, which is linked to an external web, where the user can access and analyze the collected data [10].
In 4.3 the visualization of the Sensor Web in the Huntington Botanical Gardens, which can be accessed by anyone over the internet, will be shown and discussed.

3 Information Visualization

For the visualization not only of sensor data but any data it is necessary to have a look at well-known and accepted principles of information visualization. So this section introduces a data type taxonomy of information visualization as well as tasks, user normally want to perform on visualizations, based on findings of Shneiderman.

3.1 A data type taxonomy

There are many different ways to visualize data like graphs, charts, maps and diagrams [13]. Depending on the given data there has to be chosen a visualization, that is most suitable.
In this context Shneiderman [19] as well as Card et al. [9] present a taxonomy of information visualization based on data types. Seven such data types are proposed by Shneiderman:

- 1-dimensional
- 2-dimensional
- 3-dimensional
- Temporal
- Multidimensional
- Tree
- Network

Card et al. use the same taxonomy except for temporal data, as they only deal with the use of space when encoding abstract data.
Each item of a data type has among all of its attributes certain attributes, that assign it to this very same data type. Every data type provides certain presentation and interaction techniques as well as problems concerning the user.
1-dimensional data can be regarded as linear data, mostly lines of text arranged sequentially. The presentation depends on chosen font, color or size, while interaction contains overview, scrolling or selection. The users problems include finding an item or items with certain attributes.
2-dimensional data items are placed on a plane or map, whereby the scale is an important factor in presentation and interaction. Finding adjacent items or paths between items as well as accessing an items remaining attributes can become problematic for the user.
A real-world object with volume and relationships to other objects is assigned to 3-dimensional data. It is hard to represent 3-dimensional data due to the many problems in respect of the user like for example orientation in 3-dimensional-space or recognizing above/below and inside/outside relationships.
If an item holds a start and an end time, it belongs into the temporal data type. A common presentation would be a time line where the user has to cope with finding items in a certain time period or moment and with overlapping items.
Multidimensional data can be found in most relational databases, where items have n attributes and are therefor n-dimensional. A way to visualize those data is to lower down dimension to two and use 2-dimensional visualisation in combination with a way to access the remaining attributes like multiple views. This accessing can build a problem for the user besides finding correlations or clusters among the items.
A tree is a hierarchy, where each item is linked to one parent item (except for the root). Attributes can be held by the item as well as by the link. Common presentations are diagrams or treemaps. A user must deal with the number of levels or the number of children of an item as well as with the differences between items on the same or different levels.
Items, that are linked to an arbitrary number of other items, are summarized in the network data type. This type can also be visualized by node and link diagrams, but the problems of the user contain for example the search of the shortest or least costly path between two items.
Additionally there exist several variations and combinations of these seven data types [19].
Looking at 2-dimensional data a very common visualization would be graphs. But still not every 2-dimensional data can be shown in every different kind of graph. It is for example not useful to visualize independent data like the daily average temperature of one week at a certain place with a line graph, as a line graph requires a quantitative variable with continuous values as its x-axis. In this case a bar graph would be reasonable, as relative point values are compared. A third kind of graph would be a scatterplot, in which a relationship between two variables is shown, whereby several items can share the same

value at either axis [13].

3.2 Visualizing for a user

Not only the data, that need to be visualized, are important for the choice of a visualization, but also the person using it.
Besides his seven data types Shneiderman also proposes seven tasks a user generally wants to perform. These seven tasks are [19]:

Overview Gain an overview of the entire collection.

Zoom Zoom in on items of interest

Filter Filter out uninteresting items

Details-on-demand Select an item or group and get details when needed.

Relate View relationships among items.

History Keep a history of actions to support undo, replay, and progressive refinement

Extract Allow extraction of sub-collections and of the query parameters.

When designing a visualization there should always be realized those seven tasks in the presentation and ways of interaction.
Another aspect that needs to be considered is human perception with capabilities like preattentive processing. Preattentive processing means, that the human low-level visual system can detect certain visual properties in an image within 200 to 250 milliseconds. Some of this properties are for example the size, color, shape, density or intersection of items. They can be used to draw attention on a special target. Yet a combination of properties like color and shape should be avoided, as it normally cannot be detected perattentively [12].
A further characteristic of human perception is, that there exist special color encodings for certain properties, like for example the color encoding of temperature. In our culture hot temperatures are linked with the color red, while cold temperatures are linked with blue as for example can be seen on water taps. This encoding is based on psychological reasons like experiences with fire, which is red and hot, or ice, which is blue and cold. When visualizing data of a temperature sensor, it would be reasonable to stick with that encoding, which means to use a blue-to-red color scale, to avoid misinterpretations.

4 Visualizing Sensor Data

After a closer look at sensors and some principles of information visualization both topics have to be combined to achieve a visualization of sensor data. This section therefor shows how to extract usefull data out of the sensor data and how to simplyfy the choice of a suitable visualization. At the end the visualization of the existing sensor network mentioned in 2.4 will be shown and discussed.

4.1 Aggregation and extraction of useful sensor data

When it comes to the visualization of sensor data the first question to be asked is: Which data shall be shown?
In a sensor network that delivers multiple continuous data, it is nearly impossible to show all the data. At this point the needs of the user have to be considered. For example when monitoring a factory process a user is interested in abnormal data like a pressure value, that is too high.
For the extraction of usefull knowledge out of raw sensor data there can be used data mining techniques. But before this techniques can be applied, the data need to be prepared to increase efficiency. This so called preprocessing of the data includes the following four steps:
First there must be selected the relevant attributes, which shall be considered in the data mining process. Often a user is interested in spatially or temporally restricted values like the data out of a special region or period of time.
The second step involves cleaning the data, as sensor networks can produce 'dirty data'. These dirty data can be separated into two fields, namely missed readings and unreliable readings [14]. Missed readings result for example from broken nodes, nodes, which are out of power, or communication losses inside the network, while unreliable readings have their origin in broken sensors, that still deliver faulty values (so-called outliers). There might also be a kind of noise contained in the data caused by minor variations in the individual sensor values.
After the data are cleaned, they have to be reduced for example by aggregation to speed up the later process of data mining.
An additional acceleration of the data mining process will be achieved by the last step, where the dimension of the data is reduced [20].
There are several data mining techniques, which can be used on sensor data. According to [20] there can be distinguished four different tasks, the single techniques can be assigned to, by regarding the purpose of the sensing progress:
The first task would be Predictive Modeling. Thereby values measured in the past are used to design a model, which allows predictions for values in the future like for example the amount of snow in winter.
Cluster Analysis builds the second task. The goal in here is to group items of a data set by similarity of attributes. This leads to the formation of clusters, about which can be made several statements.
In Association Analysis strong co-ocurrence relationships between events are taken into account to create rules at what conditions, which means what kind of data, an event is likely to happen.
The last task is called Anomaly Detection. As its name says, it aims to discover abnormal values in a data set, which mostly allude to unusual activities in the sensed phenomenon.
2.2 contains a description how to gather data from a network. This description referes to a special computational model, namely a centralized model. This means, that all data of the network flow to a central computer, where they are treated. In large scaled sensor networks this leads to a lot of communication and therefor costs of energy and bandwidth. A different approach would be a distributed model of computation. In this case every sensor would have to compute partial results out of its measurements before communicating them to other nodes. This is more reasonable for large scaled sensor networks, but requires every sensor to have an adequate microprozessor onboard [20].

4.2 Visualizing given data

After choosing the relevant data there has to be found a visualization to present these data efficiently.
Due to the enormous variety of application areas (see *Table 1*) it is hard to assign a special visualization to a certain kind of sensed data. Instead the data are classified to narrow the range of possible visualizations and thereby simplyfy the choice. *Table 3* shows such a possible classification of given sensor data depending on their dimensions. The sensed data always have more than one dimension. As mentioned in 2.3 position and time of a measurement always play a certain role when analysing the data. So the columns of the table represent the spatio-temporal dimensions of sensor data. The temporal aspect is thereby divided into momentary, which means an instantanous on-demand value, and continous, which means values of a certain time period, while the spatial aspect is seperated into relative and absolute values (see 2.1). The columns are therefor split into four parts, as they are divided twice. The rows of the table stand for the dimensions of a sensor, which are based on the number of different sensing components a sensor can own. They can differ from 1- to multidimensional. The entries of the table consist of the data types of Shneidermans data type taxonomy [19]. This means, that a certain n-dimensional sensor with regard to the temporal and spatial aspect belongs to one of these data types. Examples for visualizations of the different data types can be found in Shneidermans paper. The temporal data type is not included, as the temporal aspect is encoded as a further dimension of the data.
As can be seen, the dimension of sensor data grows by one, when regarding the temporal progression of the value, and grows by two, when regarding the absolute position of a value, as the absolute position is thought to be given by a x- and a y-value not regarding the z-axis of

Table 3. Classification of sensor data. Columns represent the spatio-temporal aspect of sensor data, divided into relative and absolute position(, whereby the absolute position is given by a 2-dimensional value for the x- and y-axis of space,) and for each of those divided again into momentary and continuos temporal values. Rows represent the dimensions of a sensor, which means the number of its different measurands. Entries refer to Shneidermans data type taxonomy [19].

	Spatio-temporal			
	relative		absolute	
	momentary	continuous	momentary	continuous
1-dimensional	1-dimensional	2-dimensional	3-dimensional	multidimensional
2-dimensional	2-dimensional	3-dimensional	multidimensional	multidimensional
3-dimensional	3-dimensional	multidimensional	multidimensional	multidimensional
multidimensional	multidimensional	multidimensional	multidimensional	multidimensional

space.
Depending on the final dimension of the sensor data, there has to be designed a suitable visualization, that fits the needs of the user. For example a temperature sensor in a factory, that monitors the temperature of a machine to ensure its functionality, would be a 1-dimensional sensor (= temperature) with a relative position (= machine x) and a continuous measurement. Its data are therefor, regarding to *Table 3*, 2-dimensional and could be shown in a line-graph.

4.3 An existing visualization

An example of a visualization of a sensor network is shown in *Fig. 3*. There can be seen the user interface of the internet livestream of the Sensor Web pods in the Huntington Botanical Garden presented in 2.4. This webpage offers three different views on the sensor data: A temporal view, a spatial view as well as an icon view [4].

As can be seen in *Fig. 3* the temporal view shows five line graphs and an interaction panel. The line graphs show the progression of the measurement of air temperature, humidity, light flux, soil moisture and soil temperature done by the four pods 0, 5, 14 and 15 over the last 72 hours. The interaction panel offers the possibility to change the style, scale and data in the graph. Here can be changed the style of the plot (for example from lines to points), the length of the time interval, the number of pods (up to all 20) and charts (between one and five) as well as the parameters shown in the plot out of all possible measurement values mentioned in 2.4.
The location of the pods in the Huntington Botanical Garden can be seen in the spatial view. There is presented a picture of the area taken from the sky, where spots labeled with the number of a pod represent the pods. There may be mentioned, that not all pods are shown. In another interaction panel the user can choose, which value (temperature, humidity, ...) from which point of time shall be shown. The value of a sensors measurement together with its ID and the time of the measurement becomes visible in the upper right corner of the screen, when moving the mouse over the spot representing the sensor. The spots themselves are coloured in red, yellow and green, what indicates, if the measured value lies in a normal range (green), approaches a critical treshold (yellow) or has already crossed it (red). White colour means that the sensor is disabled. A click on an enabled sensor spot shows a line graph of the measurements of the last twelve hours done by this sensor.
In the icon view there can be seen five rows of 20 traffic light, each of them representing a sensor pod and each row representing a sensing parameter, which can again be chosen out of all parameters. The color of a traffic light indicates the same assignment of a value to a range, that was used for the spots in the spatial view. Also moving the mouse pointer over an icon or clicking on it has the same effect as in the spatial view. In the interaction panel there can be chosen the moment of the measurement.
As the pods can measure up to ten values (=multidimensional), have a relative position in the garden and the user is interested in continous values for the temporal view, there are multidimensional data to visualize, regarding to *Table 3*. For gaining an overview over the system and observing single pods the seen visualization is surely suitable. But

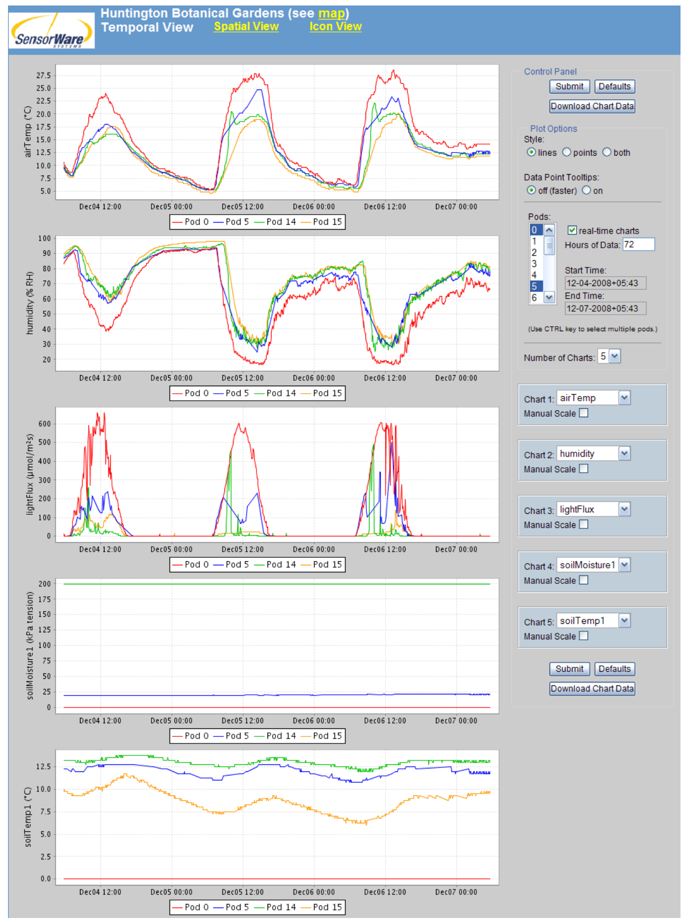

Fig. 3. Visualization of measurements of Sensor Web pods in Huntington Botanical Garden [4].

for a deeper analysis of the conditions in the Botanical Garden or the detection of certain developements other visualizations with aggregational computations might be more useful. But this visualization is open to everybody on the internet, so the scientists at the Huntington Botanical Garden will most surely have their own, better visualizations.

5 Conclusion

With the growing interest in sensor networks and their wide range of applications rises the need of meaningful visualizations of the sensed data. This paper proposes a classification of sensor data, based on the dimensions of the data and a taxonomy of visualizations by data types adopted from Shneiderman [19].
Before the formulation of such a classification there must be consid-

ered several aspects. There exists an enormous variety of measurands, that can be sensed. As a reaction on a stimulus a sensor produces an electrical signal out of which a special value is computed. Sensor nodes in sensor networks mostly contain more than one sensor and therefor produce different kinds of data. These data have to be acquired from inside the network and to be delivered to an application, which handles them. The handling can thereby consist of the storage of the data in a database as well as the visualization of the data. A visualization of data shall always contain information collected from the data, which has to be presented to the user in an understandable way. So besides the given data a visualization depends on the informations, the user wants to gain. But due to the variety of sensors grows the number of possible applications and therefor the needs of the user. Consequentially it is nearly impossible to give an always valid solution when to use which kind of visualization. Instead the focus lies on looking at the data, a sensor produces, and assigning them to Shneidermans data type taxonomy, in order to choose a visualization based on both the examples provided there and the needs of the user.
For sensor data not only the raw sensed data are of importance. Mostly it is necessary to know where or when a sensor made a measurement. Looking at the example of the Huntington Botanical Gardens in 2.4 it can only be reacted with watering on a low humidity value, which could be harmful for a plant, if it is known, where the sensor stands. The temporal aspect might be necessary to observe light flux over time and to react on a worsening of it, when a plant needs a certain amount of light. When regarding time and location values the dimension of sensor data grows. Considering this fact a classification of sensor data by the data type taxonomy can be done and visualizations realizing the needs of the user can be designed.
Further research on this topic would be necessary, for example looking on the other aspect of visualizations, namely the applications and needs of the user, and combining them with the data type classification to give appropriate solutions, when to use which visualization.

References

[1] Sensor Web Pod 14. http://sensorwaresystems.com/historical/resources/pictures/hunt-107.shtml. visited 08.01.2009.

[2] SensorWare Systems web page. http://sensorwaresystems.com/. visited 08.01.2009.

[3] TinyOS web page. http://www.tinyos.net/. visited 08.01.2009.

[4] Visualization of Sensor Web Pods. http://caupanga.huntington.org/swim/. visited 07.12.2008.

[5] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci. Wireless sensor networks: a survey. *Computer Networks*, 38(4):393–422, 2002.

[6] A. Boukerche, H. Oliveira, E. Nakamura, and A. Loureiro. A novel lightweight algorithm for time-space localization in wireless sensor networks. In *Proceedings of the 10th ACM Symposium on Modeling, analysis, and simulation of wireless and mobile systems*, pages 336–343. ACM New York, NY, USA, 2007.

[7] P. Buonadonna, D. Gay, J. Hellerstein, W. Hong, and S. Madden. TASK: sensor network in a box.

[8] C. Buschmann, D. Pfisterer, S. Fischer, S. Fekete, and A. Kröller. SpyGlass: a wireless sensor network visualizer. *ACM SIGBED Review*, 2(1):1–6, 2005.

[9] S. Card, B. Shneiderman, and J. Mackinlay. *Readings in information visualization*. Morgan Kaufmann Publishers San Francisco, Calif, 1999.

[10] K. Delin. Sensor Webs in the Wild. *Wireless Sensor Networks: A Systems Perspective, Artech House*, 2004.

[11] J. Fraden. *Handbook of Modern Sensors: Physics, Designs, and Applications*. Springer, 2004.

[12] C. Healey. Perception in Visualization. http://www.csc.ncsu.edu/faculty/healey/PP/index.html. visited 08.01.2009.

[13] M. Hearst. Information visualization: Principles, promise, and pragmatics. http://bailando.sims.berkeley.edu/talks/chi03-tutorial.ppt, 2003. visited 24.11.2008.

[14] S. Jeffery, G. Alonso, M. Franklin, W. Hong, and J. Widom. Declarative Support for Sensor Data Cleaning. *LECTURE NOTES IN COMPUTER SCIENCE*, 3968:83, 2006.

[15] S. Madden, M. Franklin, J. Hellerstein, and W. Hong. The design of an acquisitional query processor for sensor networks. In *Proceedings of the 2003 ACM SIGMOD international conference on Management of data*, pages 491–502. ACM New York, NY, USA, 2003.

[16] S. Madden, W. Hong, J. Hellerstein, and M. Franklin. TinyDB web page. http://telegraph.cs.berkeley.edu/tinydb. visited 08.01.2009.

[17] D. Niculescu et al. Positioning in ad hoc sensor networks. *IEEE Network*, 18(4):24–29, 2004.

[18] K. Römer and F. Mattern. Towards a unified view on space and time in sensor networks. *Computer Communications*, 28(13):1484–1497, 2005.

[19] B. Shneiderman. The eyes have it: a task by data type taxonomy for informationvisualizations. In *Visual Languages, 1996. Proceedings., IEEE Symposium on*, pages 336–343, 1996.

[20] P. Tan. Knowledge Discovery from Sensor Data. *SENSORS-PETERBOROUGH-*, 23(3):14, 2006.

[21] R. White. A Sensor Classification Scheme. *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on*, 34(2):124–126, 1987.

Table 2. Sensor classification by measurands [21]

super category	*sub category*
Acoustic	
	Wave amplitude, phase, polarization, spectrum
	Wave velocity
	Other (specify)
Biological	
	Biomass (identities, concentrations, states)
	Other (specify)
Chemical	
	Components (identities, concentrations, states)
	Other (specify)
Electrical	
	Charge, current
	Potential, potential difference
	Electric field (amplitude, phase, polarization, spectrum)
	Conductivity
	Permittivity
	Other (specify)
Magnetic	
	Magnetic field (amplitude, phase, polarization, spectrum)
	Magnetic flux
	Permeability
	Other (specify)
Mechanical	
	Position (linear, angular)
	Velocity
	Acceleration
	Force
	Stress, pressure
	Strain
	Mass, density
	Moment, torque
	Speed of flow, rate of mass transport
	Shape, roughness, orientation
	Stiffness, compliance
	Viscosity
	Crystallinity, structural integrity
	Other (specify)
Optical	
	Wave amplitude, phase, polarization, spectrum
	Wave velocity
	Other (specify)
Radiation	
	Type
	Energy
	Intensity
	Other (specify)
Thermal	
	Temperature
	Flux
	Specific heat
	Thermal conductivity
	Other (specify)
Other (specify)	