Visualizing Sensor Data

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Abstract— Visualizing sensor data is not a trivial task. This work tries to find a matching between sensor data and visualizations. Sensors became very popular over the last decade, they got smaller, more efficient and cheaper, that is why they spread in many fields of applications. Sensor taxonomy and the dependency of space and time will help to find visualizations for sensor data. Besides this there are problems with visualizations that will be worked out and with the results of researchers it is possible to find a mapping between sensors and visualizations. This mapping is discussed in the end of the work. It is a mapping from sensor data dimension and the dependency of the spatio-temporal aspect to the dimension of the data of the resulting visualization. With this resulting dimension it is possible (according to Shneiderman [17]) to create a fitting visualization.

Index Terms—Sensor, Visualization, Taxonomy, Data Fusion, Spatio-Temporal, Multidimensionality

1 Introduction

The field of applications where sensors are used is spreading extremely fast. The variety of sensors is increasing as much as their ease of use [5]. Since sensor data appears in large amounts and because of the multidimensionality of the data it is important to analyze this data with technical help [5]. The next step after the analysis of the sensor data is to find a visualization for the data, which is very task specific. Visualizations are important when working with sensor data, it makes it more comfortable for a user to work with the data and the data can be understood faster and easier. With a visualization it is possible to find patterns, connections or similarities in numerical data. That makes it a lot easier then to manually analyze the raw sensor data, which is sometimes impossible to understand for a person. In *Figure 1* there can be seen an example for a visualization. This one is selected from the CarTel software. The CarTel system is using sensors on mobile units to make analysis about the traffic data in certain areas [11]. A possible visualization which can be extracted from the sensed data is the presentation of traffic hot spots. On the right side there is a map with marked positions and on the left side there is a table showing the sensor values, which are linked to the marked positions on the map (see *Figure 1*). The visualization from CarTel is divided in two parts (the map and the table). Now the arising question is, whether it is possible to combine these two parts to a *single* visualization, which makes it easier and faster to receive the information. Sensor data has to be visualized, but as can be seen in CarTel System that is not a trivial task. With this idea of visualizing sensor data, there are some upcoming questions:

- How can sensor data be presented in a reasonable visualization?
- Is a mapping between sensor data and visualizations possible?
- Is it reasonable to map certain sensor kinds to a specific visualization?

Goal of this paper is trying to give guidelines for finding a fitting visualization for specific sensor data. Section 2 will discuss the taxonomy of sensors and the unique properties of sensor data. Besides this the necessity of the data fusion process (aggregation and extraction) and the importance of the spatio-temporal component of sensor data will be another important point. Section 3 will have a closer look at visualizations, how those can be classified, what is important when designing a visualization and the important role of the user and the technical devices that is used. Finally in section 4 there will be an attempt in making a matching between sensor data and visualizations. Previously challenges and problems will be discussed followed by possible starting points. Before the final matching there will be a short detour on multivariate and multiview visualizations as a reasonable solution to visualize multidimensional data.

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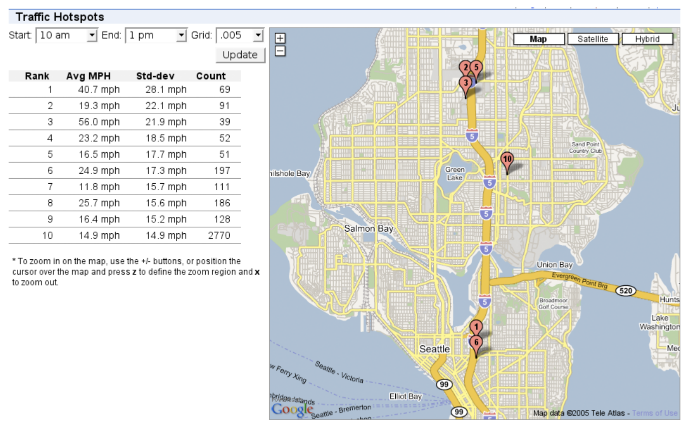

Fig. 1. The CarTel portal, showing users traffic hot spots for the Seattle area [11]

2 Sensors

This section examines the current state of the art of sensors, sensor data, sensor data fusion and the common ground of the spatio-temporal aspect in the sensed data.

2.1 Sensor Taxonomy

Sensors are not only becoming popular in scientific tasks, they are spreading in every day life tasks. Since this development is proceeding pretty fast, there are a lot of sensors nowadays [4]. In the following a classification for the large number of sensors existing is shown and the fields where this sensors are used are presented. Using White's [20] classification scheme results in the following two tables. One for the classification of the sensors and the other for the field of applications where sensors are used (see *Table 4 (at the end of the paper) and Table 1*). White is sorting the types of sensors by their measurand. This classification can help a programmer when implementing a visualization. With knowledge about the sensed value he can use fitting color scales, create specific shapes and so on (*compare section 3.2)*. The table with the field of applications can help to improve a mapping between sensor data and visualization, since it is possible to resort to previous visualizations used in similar task. As can be seen in the table, sensors are deployed in a lot of fields,

Table 1. Field of applications for sensors [20]

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

which gives a lot of visualizations already existing. White's taxonomy was made in 1987, what means that it was created about 20 years ago, so it is rather old. To consolidate his taxonomy it can be compared to [12], which is saying nearly the same as was said in 1987. There haven't been any great changes and developments in the classifying, neither on the sensors nor on the field of applications. This should make it a reasonable taxonomy for sensors nowadays. Along with dividing the sensors by its measurand, they can also be watch by functionality. On the one hand, there are *passive* sensors. These are able to generate electric signals without an additional electrical source. On the other hand, there are *active* sensors. To fulfill their task they need an external power source. Detailed and additional information on this way of classification can be found in [7].

2.2 Sensor Data

A sensor is *"a device that receives a stimulus and responds with an electrical signal"*[7]. The stimulus or measurand, was already observed in the previous section. These are usually physical or chemical forces or processes. In this part the electrical signals, with which a sensors responds, are watched. The *Handbook of Modern Sensors* [7] says, that sensors measure (in most tasks) non-electronic values and transfer these into electrical values. According to section 2.1 these values can be sensed in an active or passive way. Since in this section the data of a sensor is the interesting thing, it can be classified in another way. Measuring a value with an absolute scale, an *absolute* sensor has to be used to fulfill this task. A possible example would be the sensing process of a temperature value according to the Kelvin temperature scale, which is totally independent of the measurands. Beyond the absolute sensors there are the *relative* ones. A relative sensor generates its data according to a referencing value. Imagining to sense pressure a relative sensor can be used which senses the pressure in relation to the air pressure [7]. That means, that an application interacting with sensors needs to know with which kind of sensor it interacts, whether it is active or passive. Also it needs to know if it sends continuous data or if the data is delivered on request [1]. Wu says: *"However, different sensors may use different physical principles, cover different information space, generate data in different formats at different updating rates, and the sensor-generated information may have different resolution, accuracy, and reliability properties."*[21]. That is to say, depending on the task and the used sensors, different types of data will occur and the data will have to be computed in different ways. All in all the sensor data is only useful for a user, if he knows the context where the data is sensed and if he knows which data the sensor conveys.

2.3 Data Fusion

In sensor networks large data sets have to be handled. This can be put down to the enormous number of sensor nodes which can be used and to the continuous sensor values [1]. Data Fusion is a task that arises from this large data sets. With such large data sets there has to be a quality check of the data before making further proceedings. Sometimes it can happen that sensors are not correctly calibrated or that a sensor malfunctions. These values have to be cleaned or excluded in further proceedings [5]. After the collection of the complete data set (aggregation) and the removal of incorrect values, there has to be an extraction of the data of interest. That means an extraction of certain sensor values[19]. This two processes the aggregation and extraction of sensor data will help to find patterns in large sets of data. Having a great number of temperature sensors delivering continuous sensor values in a certain terrain and a certain time, it can be interesting for a user whether or not a certain threshold is reached. Since the user only needs a visualization of this threshold and further information like when and where it happened, the total data set of all sensors has to be aggregated (for example in a database) and the values of interest have to be extracted. If there are any values of interest then this will be visualized in an application. Another task for data aggregation from multiple sensors is radar or ultrasound examination. In these tasks there are multiple sensors used. Their data has to be aggregated before visualizing it, since the data of a single node would not make much sense to be displayed. [19] says that the data has to undergo some preprocessings, these are:

- Feature extraction
- Data cleaning
- Data reduction
- Dimension reduction

Feature extraction will select the relevant attributes or in other words the data of interest. *Data cleaning* will improve the quality of the data by reducing noise or excluding errors. *Data reduction* represents the data aggregation process. *Dimension reduction* is obviously the reduction of the number of features. All in all data fusion is important for a user, once more expressed by the following citation: *"Users will routinely require compressed summaries of large spatio-temporal sensor data. However, periodically or occasionally, users will require detailed datasets from a subset of sensors in the network"*[8]. This will lead to another important fact about sensor data, the spatio-temporal aspect.

2.4 Spatio-Temporal Component

Large sensor networks often have a lot of sensor nodes. When watching such networks it is important to know where and when these nodes measured their values. This is necessary because the sensed value has to be connected to a certain point of the network and must have a time value. Without having this information it is not possible to make any predictions or conclusions [14]. This will become clearer when watching an example. There is a temperature sensor which measured a temperature value of 40 degree Celsius. Without additional information it is only known that somewhere at some time a temperature of 40 degree Celsius was measured. Putting the sensed value in the context of a desert, then it wouldn't surprise too much that such a value was measured. Putting it in the context of the north pole it would be an extraordinary value. So the location where a sensor is used is of great importance. Staying at the example of the temperature sensor and assuming that the sensor is used in a desert, then time plays an important role, too, because temperature values can vary a lot during day- and nighttime in deserts [16]. Having a closer look at the importance of the position of a sensor it is necessary to say, that *absolute* position must be distinguished from *relative* position. Large sensor networks have multiple nodes which could be spread over a certain area. In this case the absolute position of a sensor is relevant because it would not help much to say, the sensor is at the hillside, it is necessary to know its coordinates. When watching more then one sensor node the absolute position can be important when wanting to calculate the speed of an object moving between these two nodes. Besides the absolute position there is the relative one. Relative sensors are attached to objects or persons. The interesting fact is at which object the sensor is, not its absolute position. A possible example for a relative sensor would be a door sensor [16]. As already said, time has an important role, too. This has multiple reasons. First, it is important to have knowledge about the time when a sensor measured a value to make better statements about the data. Second, time is a synchronization tool in sensor networks, therefore it is relevant to have a clock within a sensor. Lastly when watching a sensor, it can be used to show *momentary* data or to recognize *continuous* data over a certain time period [16].

3 VISUALIZATIONS

Analysis of data and getting an overview of large data sets are tasks that have to be done in every day life. Data like sensor data normally exists in numerical values so the process of understanding or analyzing it is not trivial, finding patterns seems hardly possible. To make this tasks easier there are visualizations. Visualizations take the numerical data, analyze it, use extraction and aggregation methods and then give the user a graphical representation of the input data. This representation makes it easier to understand the data and to interact in the data set. In this paper the visualization limit to sensor data. The following sections will discuss a visualization taxonomy and starting points for visualizations.

3.1 Visualization Taxonomy

Making a taxonomy for visualization is a difficult task. Since there are a a lot of visualization methods to present the same information it is not trivial to find a taxonomy for visualizations. In this work there will be a classification-scheme according to Shneiderman, who has done research work on the topic of information visualization. [17] says that there are seven different types of data to be visualized. That is a possible way to classify the types of visualizations, according to it's underlying dataset. The seven data types are:

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

1-dimensional data types are every form of linear data for example text documents. The main principle is that the data is organized in a linear way. *2-dimensional* is for example map-data like geographical maps or something similar. Data in this type have planar character and can be projected on a map. *3-dimensional* refers to real objects, Shneiderman says, "that it's about objects with volumes with some potentially complex relationship to other items" [17]. *Temporal*: This data has a start and finish time and the objects can be projected to a timeline. *Multi-dimensional* data is mostly data in databases, as sensor data is stored in databases, too, and mostly has a lot of attributes this can be of interest in further observations. *Tree*: The underlying data has a hierarchical structure and can be display in the form of a tree. Finally there are *networks*. They are similar to trees, that means there is a connection between the data elements, but not in a hierarchical way. Possible visualizations for each data type are presented in [17]. Like in *Readings In Information Visualization* [18] said, the ways of presenting data in visualizations are numerous. According to the dimensions of the data the dimensions of the visualization has to be extended. That means, that if there is a 1-dimensional set of data, then the dimension of the visualization does not need to be more then 1 (but it can be). All in all it is to say, that there exist a large number of visualization techniques and that they develop every day so a listing of all would be impossible. That is why the taxonomy was made by the dimensions.

3.2 Visualization Guidelines

This section examines two points. First, there are certain principles that can help in designing visualizations, such as shape, color, etc. which apply to human cognition. Second, there are some representative scales in every day life for visualizing special things like temperature, which is normally displayed with blue for cool temperatures and with red for hot ones. According to [10] there are certain perception properties every person has in common. For example if it is about finding an object in a large amount of objects. If the object has a unique color or a unique shape it can be found pretty fast. These perception rules should be kept in mind when trying to design a user interface of good quality. Using them will make it easier for a user to find outliers in a large data set. This and similar tasks can be simplified with the utilization of perception rules. A great overview of a lot of rules is given in [10], since the listing and discussion of all of them would go beyond this work. Apart from that, some typical design patterns occur in every day life. These patterns are not forced to be used but in most cases they are used since it is common sense. The most popular example will possibly be the mapping of temperature to a color scale from blue to red. Another example would be brown and green scales which represent height values on maps. So when designing a visualization for sensors which are measuring temperature values it would be reasonable to use the mentioned color scale. Another example would be a traffic light, where the color red represents the signal for stopping and green is the signal for going. Combining the principles of human cognition with the common ways of visualizing certain data will help to create good and easy to understand visualizations.

3.3 Customized Visualizations

As already shown in the previous section there are a lot of things that have to be regarded when visualizing information. In this section the user and the hardware will be discussed in short as another starting point to create visualizations. One great factor for the design of a user interface is the interface, in other words, the hardware. Showing a map on a PDA is not easy since the PDA has a rather small display and the information shown on it has to be reduced to a certain amount so that it is easy to understand. Showing the same map on a large (television-like) display there can be shown much more information as will be displayed on a PDA. The field of applications for sensor data is wide spread (compare section 2.1) so it is likely that the hardware varies. Watching the CarTel example from the beginning [11] the data that is sensed can be displayed on a normal device like a PC or a notebook. Taking a closer look, the data gathered from the sensors is traffic data and is interesting for the participants of the traffic system. Because of this it makes sense to display the data in an in-car-system. This is only one example for the importance of customized visualizations depending on the hardware used for showing the information. Besides the hardware there is the user himself who needs to be regarded for the development of a visualization. A user can be uneducated in the topic which will be visualized. That is the reason why it is important, that the visualization consists of low complex parts, that there is additional information on demand, and further methods to add information. Having a specialist watching the same data, a different visualization could make much more sense, since he has much more knowledge about the topic. Interface and user are one big factor that influences the creation of a visualization. Additionally there are the guidelines of the previous section which have to be fulfilled. With this two big problems the design of a visualization is not a trivial task.

4 Matching between Sensor Data and Visualization

The final part of this work is to find a possible matching between sensors and visualizations. Before doing this, there has to be a short overview of problems which can occur when trying to visualize sensor data. Trying to connect the topics sensor data and visualization to give advice for the visualization of sensor data is the goal in this section.

4.1 Challenges and Problems

Trying to visualize sensor data there will be a confrontation with challenges and problems. A closer look at sensor networks will be made to explain this in more detail. [4] is saying that when having a large network of sensor nodes and there are for example two targets which are watched by the sensors, then each node in the network is giving a different identifier to one of the objects. When trying to visualize the data later a programmer needs to know which data is referring to which object. Another challenge is the sensor network itself. The lifetime of such a network is limited by the energy resources of the nodes. When there is a lot of communication or processing then the nodes will be unable to sense data for long periods. Along with the lack of energy there is the problem of the reliability. That means the problem of noise in sensor data or the collecting of wrong values. All this problems occur when trying to visualize the sensor network data [4]. According to [5] there are additionally some unique properties of sensor data which will make problems in the process of visualizing them, partly they are covering with [4]. The two largest problems of sensor data are, that they appear in a large amount and that the data itself is multidimensional. Another problem is, as already mentioned, noise or failure of sensors. Since it can happen that sensors stream their data, this has also to be taken in regard when implementing a visualization. [5] and [4] both say, that sensor data can sometimes be gathered 'on-the-fly' according to an example of Chong this can happen when an airplane flies over a surveillance area and sends a query to the sensor nodes. It can not been taken for granted that there is a 100% reliability of the sensors to answer the query. Beyond the sensors itself there are problems when designing visualizations. The biggest problem according to [15] is the fitting of a visualization to the wishes of the user, to the task and to real world problems. Trying to display the data there should be different views on the same data set. This features have to be implemented and the properties of sensor data have to be regarded to have a good visualization of sensor data. As can be seen there are a lot challenges when visualizing sensor data.

4.2 Starting Points

There are multiple starting points when trying to find a visualization for sensor data. This work will take a look at some of them, partly described in earlier sections. One possibility to start would be the taxonomy of the sensors watching the sensor task in special. This will become clearer with the following examples. The first one is about wearable sensors which should help within avalanche rescues [13]. As can be seen here, the interesting thing is a single sensor value which is showing the position and the vital signs of the victim buried in snow. So in this case a visualization will need a *single* sensor to be displayed. A possible visualization was given in the paper (compare *Figure 2*). The second example is about understanding the environment, therefore there are multiple sensors used [6]. If this data will be displayed the task is different from the first one because the interesting data is not located in a single node. It is distributed in a large number of nodes. To make sense of the total data, there has to be shown more then the values of one node (as can be seen in *Figure 3*). As can be seen, there is a dependency between the task and the visualization, so the task of the sensor is one starting point. Another starting point can be found in the topic of information visualization. According to Shneiderman there is the '*Visual Information Seeking Mantra*' [17]. He says, that this is a starting point to create a good visualization. There are four steps, that have to be done, when creating a design, these are:

- Overview first,
- zoom and filter then
- details-on-demand

These four steps are explained in detail in [17]. The main principle is to give an overview of the whole data set. To take a closer look at special data there a tools that allow zooming functions or which filter away uninteresting data. If the user wants to have details about the data, there should be a possibility to get these details. To get a better understanding of this four steps there will be a short example. A sensor is measuring a lot of values, for example temperature, barometric pressure, humidity and so on. Then all these values are displayed in one big graph (that would be the overview). Zooming in on a special week and filtering out all values but temperature would refer to zoom and filter. Lastly if the user is interested in a single value on a special day of this week, this would be the details on demand, where additionally the other values can be shown, too. Shneiderman's Mantra was a second starting point to find or create a good visualization. A third point would be the spatio-temporal aspect of sensor data (section 2.4). In short words, there are special ways to visualize spatial data and temporal data[18]. This visualization techniques can be used as a starting point to create an own visualization.

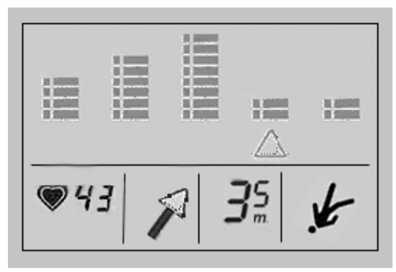

Fig. 2. Avalanche rescues: Screen sketch for liquid crystal displays [13].

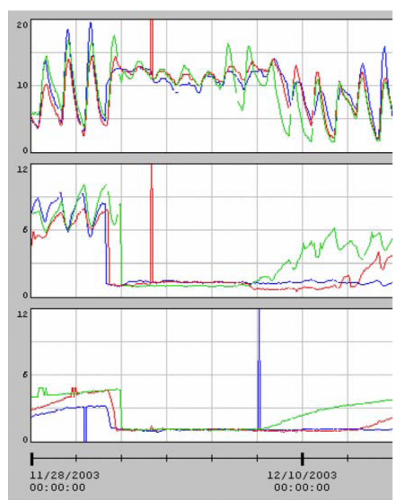

Fig. 3. Overview over three sensor pods(each color represents a pod) [6]. Graphs show (top to bottom): surface temperature (degree Celsius), surface moisture, and soil moisture at 0.5 m depth

4.3 Multivariate and Multiview Visualization

Multidimensionality is one of the biggest problems when visualizing sensor data [5]. A lot of sensors measure more then one

Table 2. High-dimensional visualizations[9]

Visualization type
2D and 3D scatterplots
Matrix of scatterplots
Heat maps
Height maps
Table lens
Survey plots
Iconographic displays
Dimensional stacking (general logic diagrams)
Parallel coordinates
Line graph, multiple line graph
Pixel techniques, circle segments
Multi-dimensional scaling and Sammon plots
Polar charts
RadViz
PolyViz
Principal component and principal curve analysis
Grand Tours
Projection pursuit
Kohonen self-organizing maps

kind of data at a time. For example it senses temperature, air pressure, humidity and so on. Displaying all these values of the sensors from a large area is getting really difficult. This leads to the usage of multivariate and multiview visualizations. The official definition of a multiple view system, according to Baldonado, is: "*We say that views are distinct if they allow the user to learn about different aspects of the conceptual entity, e.g., by presenting different information, or by emphasizing different aspects of the same information. A multiple view system uses two or more such distinct views to support the investigation of a given conceptual entity*"[3]. Returning to the weather example, that would mean, that there is a view showing the temperature data of a single sensor. Another view displays the sensor's humidity value and a third view could for example show a map of all sensors and their current temperature values. The target of this multiple view displays is to reduce the dimension of the data by showing it in more then one view. Multivariate visualizations are another way to present n-dimensional data sets besides the multiple view displays [9]. That makes them important for the presentation of sensor data, which are often, like seen earlier in this paper, of multidimensional character. Table 2 is adopted from [9] and gives an overview of high-dimensional visualizations which mostly can be used for the visualization of sensor data. Grinstein is presenting detailed information on all named visualizations in his paper [9]. Since this work is not handling multivariate visualizations and the information is not relevant for the mapping it is not shown here. The importance of multiview and multivariate visualizations is not only given because of the multidimensionality of the data, but additionally because of the dependency of time and space of the measured value. An absolute location value can have up to three dimensions which are interesting for the user. Those will have to be presented in a visualization plus the temporal aspect. That means, that the visualization techniques presented, in short, in this section are really important.

4.4 Mapping

This last section is trying to provide a mapping between sensor data and visualizations. This mapping is a new contribution and is created from the results of the previews work, most influenced by Shneiderman's data type classification which was presented in section 3.1. Table 3 is showing a possible mapping from sensor data to visualizations. Its idea is to project the dimension of the measurands and the dependency of space and time on the visualization taxonomy by data type from Shneiderman [17]. One axis of the table is representing the dimension of the measurands, the other is representing the spatio-temporal dependency of the sensor value. The dimension of the measurands serves as a base for the resulting data type (compare to section 3.1). If the dimension of the measurand is 1 then the data type is 1-dimensional, too, according to Shneiderman [18]. Adding the spatio-temporal aspect of sensor data to the dimension of the measurand, the final data type will be extended. Referring to section 2.4 the position of a sensor is absolute or relative. Having a relative position, it is not necessary to extend the dimension of the data type. A simple label with information about the relative position is enough. Absolute position however extends the dimension. Assuming to have 2-dimensional position values, it is necessary to display the x- and y-position of the sensor data value. So, the data type dimension will be extended by 2. Besides the position there is time as another influence factor on sensor data. Also shown in section 2.4 sensors measure values continuous or momentary. A sensor, which registers momentary values does not extend the dimension of the resulting data type, since the information is always displayed immediately on the screen and no temporal information has to be encoded. Continuous sensors do have to record information over time and these values have to be displayed. A timeline will extend the resulting data type dimension by 1. The measurands' dimension together with the spatio-temporal aspect can be mapped to Shneiderman's taxonomy by data type. This taxonomy gives advice for a possible visualization [17]. The resulting matrix (compare table 3) contains four data types 1-dimensional, 2-dimensional, 3-dimensional and multi-dimensional (abbreviated by 1-d, 2-d, 3-d and multi-d). For each of this data types Shneiderman is presenting ideas and possibilities how to visualize the data. An example from the earlier presented avalanche rescues is showing a sensor which is measuring the heart rate among other values. The sensor data itself is 1-dimensional (only regarding the heart rate). Besides the sensor data there is the position of the sensor which is relative in this case (it is only interesting who is wearing the sensor) and the temporal aspect of the sensor value which is continuous. According to the matrix the resulting data type is 2-dimensional since the input values are 1-dimensional sensor data and relative-continuous dependency. With the proposal for a data type it should be possible to create a visualization (compare [17]). Figure 4 is showing a visualization chosen in [13] to display the heart rate over a certain time.

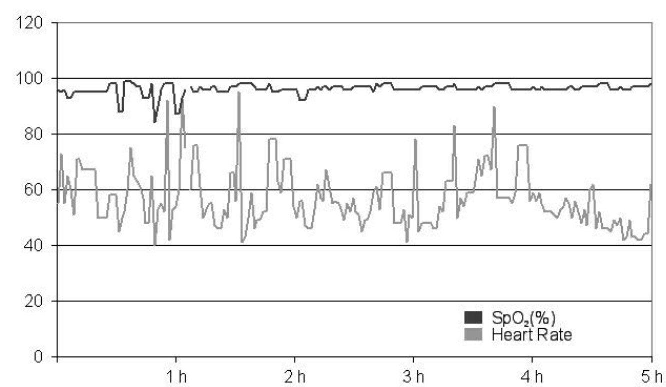

Fig. 4. Oximeter measurements [13] (in this case only the heart rate is of interest)

5 Conclusion

Having found a possible mapping from sensor data to visualizations in this work, it would be recommended to prove this matching with a large study. Different combinations of sensor data with different dependencies of space and time should be tried out and be visualized according to the resulting data type. Since Shneiderman only gave a taxonomy by data type for the visualizations [17] the final word of how to implement the visualization is not yet spoken. Some of the mentioned starting points can

Table 3. Mapping of sensor data to visualizations. The cell entries represent the dimension of the resulting data type of the visualization according to Shneiderman [17].

	1-dimensional	2-dimensional	3-dimensional	multi-dimensional
relative-momentary	1-d	2-d	3-d	multi-d
relative-continuous	2-d	3-d	multi-d	multi-d
absolute-momentary	3-d	multi-d	multi-d	multi-d
absolute-continuous	multi-d	multi-d	multi-d	multi-d

help in developing visualizations. But since the field of sensors grew pretty fast over the last years (compare [4]) it is probable that in the future sensors will be different from sensors nowadays. This could lead to totally different ways of visualizations, which are not thinkable of right now. Besides the sensors there is the visualization hardware which will introduce new possibilities in future. This technical progress makes it difficult to give a mapping between this two topics. An up to date example of this changes is augmented reality. Augmented Reality is briefly said the extension of the real world with virtual elements [2]. To extend the real world there need to be sensors in the user's environment that can sense his behavior so that an interaction between real world and computer is possible. The sensed behavior will undergo certain processes and finally there will be some output in different kinds of visualizations. All in all it can be said, that hardware (both sensors and computers) and software is developing really fast and tasks extend to a lot of fields (for example the augmented reality). Beyond this sensors are used in different tasks and in different ways, what will make a unique visualization of a specific sensor impossible. As a conclusion there can be said that it is possible to make an assignment from sensors to visualizations regarding the dimension of the sensor data and the data type of the visualization. However it is not possible to make statements about the look and feel or the interaction methods of the visualization. It is advisable to design a visualization that resorts to typical every day life and widely used visualizations, which an ordinary user can easily understand.

REFERENCES

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

[2] R. Azuma et al. A Survey of Augmented Reality. *PRESENCE-CAMBRIDGE MASSACHUSETTS-*, 6:355–385, 1997.

[3] M. Baldonado, A. Woodruff, and A. Kuchinsky. Guidelines for using multiple views in information visualization. In *Proceedings of the working conference on Advanced visual interfaces*, pages 110–119. ACM Press New York, NY, USA, 2000.

[4] C. Chong and S. Kumar. Sensor networks: evolution, opportunities, and challenges. *Proceedings of the IEEE*, 91(8):1247–1256, 2003.

[5] D. Cook. Making Sense of Sensor Data. *IEEE PERVASIVE COMPUTING*, pages 105–108, 2007.

[6] K. Delin, S. Jackson, D. Johnson, S. Burleigh, R. Woodrow, M. McAuley, J. Britton, J. Dohm, T. Ferré, F. Ip, et al. Sensor Web for Spatio-Temporal Monitoring of a Hydrological Environment. In *35th Lunar and Planetary Science Conference, March 15-19, 2004, League City, Texas, abstract*, 2004.

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

[8] D. Ganesan, D. Estrin, and J. Heidemann. DIMENSIONS: Why do we need a new Data Handling architecture for Sensor Networks?

[9] G. Grinstein, M. Trutschl, and U. Cvek. High-dimensional visualizations. In *Proceedings of the 7th Data Mining Conference-KDD*, 2001.

[10] C. G. Healey. Perception in Visualization. 2007.

[11] B. Hull, V. Bychkovsky, Y. Zhang, K. Chen, M. Goraczko, A. Miu, E. Shih, H. Balakrishnan, and S. Madden. CarTel: a distributed mobile sensor computing system. In *Proceedings of the 4th international conference on Embedded networked sensor systems*, pages 125–138. ACM Press New York, NY, USA, 2006.

Table 4. Sensor classification by measurands [20]

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)	

[12] R. Luo, C. Yih, and K. Su. Multisensor fusion and integration: approaches, applications, andfuture research directions. *Sensors Journal, IEEE*, 2(2):107–119, 2002.

[13] F. Michahelles, P. Matter, A. Schmidt, and B. Schiele. Applying wearable sensors to avalanche rescue. *Computers & Graphics*, 27(6):839–847, 2003.

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

[15] C. Plaisant. The challenge of information visualization evaluation. In *Proceedings of the working conference on Advanced visual interfaces*, pages 109–116. ACM New York, NY, USA, 2004.

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

[17] 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.

[18] B. Shneiderman, S. Card, J. Mackinlay, and B. Shneiderman. *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann, 1999.

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

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

[21] H. Wu. *Sensor Data Fusion for Context-Aware Computing Using Dempster-Shafer Theory*. PhD thesis, Carnegie Mellon University, 2003.