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Sensor Data and Managing Data Quality in Sensory Network Applications

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ABSTRACT
The concept of pervasive computing has become a reality. Sensors and sensory networks are becoming a vital part of organizational infrastructures as they allow integration of real-time data. The sensors have the potential to provide vastly distributed real-time data. But they also have certain limiting characteristics that can impact the quality of data collected over a sensory network. The first objective of this paper is to identify the implications for data quality of sensors and sensory networks. The second objective of this paper is to describe a method for managing data quality in sensory networks using the information product approach. Finally, to help organizations effectively deploy sensory networks, we present a conceptual framework to better understand the advantages and drawbacks of sensory networks.

Keywords
Sensor, Sensory Networks, Data Quality, Data Quality Dimensions, Data Quality Management.

INTRODUCTION
The concept of pervasive computing has become a reality. Sensors and sensory networks are finding numerous applications in everyday life. Such applications include network traffic management (Babu, Subramanian and Widom, 2001; Gehrke, Korn and Srivatsava, 2001), fraud detection (Gehrke et al., 2001), medical applications for monitoring vital signs and prescribing medications (Carney, Cetintemel, Cherniack, Covey, Lee, Seidman, Stonebraker, Tatbul, and Zdonik, 2002), financial analysis (Parker, Muntz, and Chau, 1999), detecting and reporting emergency situations such as chemical leaks (Carney et al., 2002), building monitoring (Madden and Franklin, 2002), tracking wild-life and habitats [Berkeley Intel Lab.’s Great Duck Island Project, Princeton’s Zebratracker Project], as well as monitoring traffic conditions [Berkeley’s PATH, OSU’s Traffic]. Sensors and sensory networks allow integration of real-time data. They can support the capture and communication of vastly distributed real-time data. They also have several limiting characteristics: they have limited power resource, they are sometimes unconnected to the Internet, their topology is very dynamic, and the communications (between sensors, and between sensors and base stations) is un-reliable. They produce a continuous stream of data that databases have difficulty managing. In some cases data need not be stored while in others data must be stored to support decision-tasks.

This paper focuses on stored sensor data and its implications for managing data quality. The quality of decisions made is heavily dependent on the quality of data used in decision-making. The huge volume of information produced, transferred, processed and stored every day does not meet the required quality standards. The Internet, mobile technologies, wireless devices, and sensory networks have increased the volume of data while permitting decision-makers to access in real time, information that is widely distributed. The impact of such environments on data quality is a research issue that needs to be well understood for data quality management. The first objective of this paper is to identify the implications of sensors and sensory networks for data quality. The second objective of this paper is to describe a method for managing data quality in sensory networks using the information product (IP) approach. We illustrate how sensory networks can be represented using this approach and then how quality can be evaluated within this representation. Finally, to help organizations effectively deploy sensory networks, we present a conceptual framework to better understand the advantages and drawbacks of sensory networks.

Viewing information as a product for managing information quality has received considerable attention in the recent past. Significant research contributions that adopt the IP approach include defining quality measures for information products (Ballou, Wang, Pazer and Tayi, 1998), principles for managing information as a product (Wang, Lee and Strong, 1998), identifying benchmarks for information quality (Kahn and Strong, 1998), and defining a representation scheme for visualizing the manufacture of an IP (Shankaranarayanan, Wang and Ziad, 2000). A fundamental notion underlying the IP-
approach is that data1 (or information) that is the output of a query is an IP that is created (manufactured) from raw materials (raw data streaming from sensors) using processes (bay stations that receive and forward it, processes that capture, format, filter, and/or transform such as the query), and intermediate storages (databases, files). Treating information as a product in sensory networks raises interesting questions. For instance, the product in a sensory network may be consumed as it is being produced (e.g. continually running queries that demand current temperature of an engine and the delta-change from the previous reading every five minutes to determine if the engine needs to be slowed down or shut-off). What if the information product is used in a “what-if” analysis where the consumer, by changing some data values, is re-creating the product with a different “flavor”? Not only is the data capture dynamic, the decision-making and analysis is also dynamic in sensory networks. In this research we attempt to examine these characteristics to determine their impact on data quality.

The remainder of this paper is organized as follows. Section 2 presents an overview of research in two relevant areas: sensory networks and data quality, to distinguish the contributions of this paper. Section 3 describes the properties of sensors and sensory networks and identifies how it impacts data quality. A method for managing data quality in sensory networks is proposed in section 4. A conceptual framework to understand the deployment of sensory networks along with the conclusions is presented in section 5.

RELEVANT RESEARCH

A sensor transforms energy of different types into sensor data that is the output of a sensor. A smart sensor such as the MOTE [SmartDust Project UC-Berkeley] besides having the capabilities of a sensor includes computing and communication capabilities. It can store, locally process, and transmit/communicate data that it produces. This paper assumes that all sensors are smart (or will be in a short time). Limitations of sensors and sensory networks include:

- Limited energy - sensors are typically powered by non-renewable batteries and changing batteries is infeasible given the location of the sensor and the nature of the network.
- Limited processing power – sensors typically have low processing capacity (4MHz), low memory (e.g. 8K program memory and 512 bytes of SRAM), and do not have persistent storage. This restricts the type and amount of processing that can be performed.
- Limited bandwidth – sensors use wireless channels for communication. The low power availability and the number of sensors in a network result in each sensor having a low channel bandwidth and a limited range.
- Limited measurement capability – a sensor typically measures one property (e.g. temperature) due to the constraints imposed by the size, power, energy, and communication limitations.
- Limited reliability – individual sensors are typically unreliable. The cost and size of sensors today permit applications to have networks with a large number of sensors in an attempt to improve fault tolerance and increase reliability. This may cause redundant capture of data. Further, as some sensors die or are unable to communicate, other sensors in the network must dynamically reconfigure themselves to define the network.
- Limited to streaming data – sensors typically push data in streams at well-defined time intervals and sometimes without being explicitly asked for the data. This creates problems with data storage and data is often processed/queried in real-time.
- Limited security – as sensors transmit data over wireless networks the data needs to be secured. Given that sensors do not have high processing power, standard algorithms used for encrypting data may not work. An important research stream in sensor networks is attempting to find alternate encryption algorithms that are processing and energy efficient.

The above characteristics of sensors have a strong impact on the quality of data and data quality management in sensor networks. We attempt to identify their impact in terms of specific data quality dimensions. Research has illustrated that data quality may be evaluated along several different dimensions (DeLone and McLean, 1992; Wang and Strong, 1996; Redman,

1 Though it is recognized that there is a difference between data and information (processed data), this paper treats data and information interchangeably as it does not impact the concepts and discussions presented here.
1996). Fox et al. (1994) discussed four important dimensions of data quality: accuracy, completeness, consistency, and current-ness. Miller (1996) identified ten dimensions of information quality including accuracy, timeliness, completeness, and relevancy. Based on a two-stage survey, Wang and Strong (1996) analyzed and identified the multiple attributes of data quality from data consumers’ perspective. They grouped the attributes into four categories: intrinsic, contextual, representational and accessibility (See Table 1).

<table>
<thead>
<tr>
<th>Category</th>
<th>Intrinsic data quality</th>
<th>Accessibility data quality</th>
<th>Contextual data quality</th>
<th>Representational data quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimensions</td>
<td>Accuracy</td>
<td>Accessibility</td>
<td>Timeliness</td>
<td>Interpretability</td>
</tr>
<tr>
<td></td>
<td>Objectivity</td>
<td>Security</td>
<td>Completeness</td>
<td>Ease of understanding</td>
</tr>
<tr>
<td></td>
<td>Believability</td>
<td>Ease of operation</td>
<td>Relevancy</td>
<td>Concise representation</td>
</tr>
<tr>
<td></td>
<td>Reputation</td>
<td></td>
<td>Value added</td>
<td>Consistent representation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Amount of data</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Data Quality Categories and Dimensions Model of Wang and Strong (1996)

Although useful, conventional approaches to data quality management such as data cleansing (Hernandez and Stolfo, 1998), data tracking and statistical process control (Redman, 1996), data source calculus and algebra (Lee, Bressen, and Madnick, 1998), data stewardship (English, 1999), and dimensional gap analysis (Kahn, Strong and Wang, 2002) do not provide a systematic approach for managing data quality in-use that is needed for sensory networks. In this paper, an alternative approach based on the notion of an information product (IP) is proposed for managing data quality in sensory networks. The IP approach permits sensor networks to be conceptualized as a “product-line” – each sensor as a provider of raw data, data filtering and aggregation as processes, and databases as intermediary storages. It allows the visualization of the network and its components that the administrator can use to monitor the data and its quality as it flows through the network. The IP can conceptualize the flow of information that is typical in sensory networks - across business units and organizational boundaries. A query (whose output is an IP) can combine data provided by multiple sensors and the same query might use data from different sensors at different points in time because sensors might reconfigure themselves dynamically within the network. Further, multiple query-outputs may share a subset of processes and data inputs, and may be created using a single “production line” with minor variations that distinguish each IP. To exploit these properties of IPs and to manage data quality using the IP-approach, mechanisms for systematically representing the manufacturing stages, and for evaluating data quality at each stage are essential. This paper uses the IPMAP, a modeling scheme that permits explicit representation of the manufacture of an IP (Shankarnarayanan et al., 2000). It allows the decision-maker to visualize not only the widespread distribution of data and other resources in the sensory network but also the flow of data elements and the sequence by which these data elements are processed to create the IPs.

DATA QUALITY IMPLICATIONS

This section looks at the characteristics of sensory networks to understand how each characteristic impacts data quality. Table 2 presents a summary of the characteristics and the implication of each for data quality management.

**Instantaneous** – sensors capture data and communicate it without delays. Data from a sensor is available instantaneously for use by data consumers. Timely data is hence always accessible from the sensory network.

**Automated** – there is no manual intervention in the “transfer” of data from a sensor to a sensory network (in case of streaming data) or to a data repository. This improves the accuracy of data as the traditional errors in data capture due to human involvement are eliminated.

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2 This list is not exhaustive but does cover a majority of the key properties and implications. As sensory networks are better understood, more properties and implications may be identified and included.
Data Streams – sensors transmit data at well-defined time intervals but in continuous streams. Often, data is pushed into the network without it being demanded. In traditional networks data is pulled by a request. This information push can result in information overload as the user/database face a torrent of data. The onus to distinguish what is relevant and what is not is on the user/database. Research addressing data aggregation in sensory networks has shown that some intelligence can be built into the network to reduce this overload.

Connectedness – sensors have a limited power source. Transmission consumes more power than processing within sensors. Sensors in a network can lose all of the power and die of exhaustion. If a sensor dies, the other sensors in the network need to dynamically reconfigure themselves to ensure connectivity and to provide the same data the now-dead sensor was responsible for. Limitations in bandwidth and range combined with the wireless channels used to connect the sensors further decrease the reliability of the network. This implies data loss, as not all transmissions are successful resulting in low data completeness. Transmission losses negatively impact the accuracy of the transmitted data as well.

<table>
<thead>
<tr>
<th>Property of Sensors and Sensory Networks</th>
<th>Implications for Data Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instantaneous</td>
<td>Timeliness (+) – the most current data is always accessible.</td>
</tr>
<tr>
<td>Automated</td>
<td>Accuracy (+) – traditional errors in data capture due to human-involvement are eliminated</td>
</tr>
<tr>
<td>Data Streaming</td>
<td>Relevance (-) – there is an overload of information and the user/database faces a torrent of data. The onus to distinguish what is relevant is on the user/database</td>
</tr>
<tr>
<td>Connectedness</td>
<td>Completeness (-) – not all data transmissions may be successful resulting in missing data.</td>
</tr>
<tr>
<td></td>
<td>Accuracy (-) – inaccurate data values may be transmitted and stored.</td>
</tr>
<tr>
<td>Continuous Tracking</td>
<td>Completeness (+) – more complete information about the location/movement of the object being tracked. The extent of “completeness” is determined by the time-interval that can be defined by the user/usage of the data</td>
</tr>
<tr>
<td>Format</td>
<td>Representation Consistency (+) – data is captured, transmitted and stored in a consistent manner</td>
</tr>
<tr>
<td>Portability</td>
<td>Believability (+) – the source of the data is clearly identifiable regardless of whether the source is stationary or moving.</td>
</tr>
<tr>
<td>Identity</td>
<td>Trace-ability (+) – quality issues with data can be tracked to a source</td>
</tr>
<tr>
<td>Understanding data loss</td>
<td>Reliability and Believability (-) – unknown causes negatively impact the reliability of the data and consequently is believability</td>
</tr>
<tr>
<td>Data Redundancy</td>
<td>Accuracy (-) - More than one sensor can respond (assuming they can all satisfy data request) resulting in redundant data</td>
</tr>
<tr>
<td>Data Aggregation</td>
<td>Timeliness (-) – aggregation causes delays in data delivery. This affects timeliness in real-time systems and may not have a significant impact on business systems</td>
</tr>
</tbody>
</table>

Table 2: Properties of sensory networks and implications for data quality

Continuous tracking – sensors track data continuously defined by preset time intervals. The smaller the interval the more continuous is the data collected. Hence more complete information about the object being tracked is available for use by queries. The extent of completeness is defined by the time interval for data transmission.
Format – a homogeneous set of sensors captures and transmits data using a defined format that is consistent across the set of sensors. The representational consistency of the data in the network is improved as all these sensors capture, communicate, and store data using the same format.

Identity – each sensor in a sensory network can be uniquely identified and associated with the data that sensor captures and communicates. Even though this property of sensors is not utilized for routing in sensor networks due to other difficulties it is of great value in managing data quality. This property improved data trace-ability. If a data quality problem is identified in a sensory network, the identity of a sensor can be used to determine which sensor (or sensors) were responsible for capturing and transmitting the problematic data.

Understanding data loss – queries that run against sensor-data have predicate conditions associated with them. For example a query could ask for the number of automobiles that passed a certain sensor located on a highway to be transmitted every 10 minutes. It could have a predicate condition that asks for this transmission only if the number of cars exceed ten. If data is missing at a specific time (say 9:30 am), was this because of a transmission error or because the number of cars that passed this sensor was less than ten? Research in sensory data management is attempting to offer solutions on how queries can make sense of this data loss problem. However, such unknown causes for data loss negatively impact data reliability and consequently data believability.

Data redundancy – an individual sensor is inherently unreliable due to its limitations described earlier. To improve reliability, multiple sensors are deployed in a sensory network. As a result, data describing a single object may be transmitted by more than one sensor at any given point in time. No two sensors are located in the same place and due to differences in positioning, data describing the same object transmitted by two different sensors may have differences in values. This negatively impacts data accuracy and the user has to make intuitive decisions to determine which reading is more accurate.

Research on data aggregation is offering “in-network” solutions to eliminate data redundancy in sensory networks by performing data aggregation inside the network so that applications/users see just one record for an object at a given time instead of many different ones.

Data Aggregation – the data aggregation performed “in-network” to eliminate data redundancy also causes network delays. These delays may be significant depending on the domain of application of the sensory networks. It is unlikely that the aggregation delays would have an impact within business domains as these are in the order of microseconds. Nevertheless, delays will have a negative impact on the timeliness dimension of data quality.

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MANAGING DATA QUALITY

We illustrate the application of the IPMAP to represent a sensory network using a sample scenario of an emergency management situation. Consider an IP (a report providing the current status of resources) generated for an emergency management service (EMS) coordinator and used to decide the allocation of victims/patients to ambulances and direct ambulances to available emergency rooms (ER) in nearby hospitals. The creation of this report is shown by the IPMAP in figure 1. Sensors (shown as data sources DS₁, DS₄, and DS₅) attached to victims monitors and transmits the vital signs. This data is then captured and forwarded by a bay station (shown as process P⁴) and a snapshot of the vital signs combined is created by yet another process P⁴. The paramedic (data source DS⁵) provides observations of victim’s conditions, treatments provided, and recommendations that is captured (by process P⁵). The snapshot and EMT recommendations are combined for each victim (by process P⁶) and stored in a database (data store S¹). The GPS on ambulances (shown as data source DS²) provides location information and this is combined with traffic conditions (data source DS⁴) to estimate (process P⁶) the arrival time of the ambulance at the site that is captured in the database. The hospital ER (DS⁷) provides its status (beds available, resources available, whether open/closed etc.) which is also captured (by process P⁶) in the database. Finally, the current condition report is generated by the process (P⁷) and displayed to the coordinator (shown as the data consumer DC¹).

The IPMAP is also capable of showing how data spans organizational boundaries (e.g data from the hospital to the emergency site and data from traffic sensors used by the emergency site) and these are shown as OB¹ and OB² in figure 1.
In the IPMAP representation, an input obtained from a source is referred to as a raw data unit. Once a raw data unit is processed or inspected, it is referred to as a component data unit. The final product may be made of both raw and component data units. The information system boundary construct and the organization/business unit boundary construct represent the flow of data units across information systems and organizational boundaries respectively. Each construct is supplemented with metadata about the manufacturing stage that it represents. The metadata includes (1) a unique identifier (name or a number) for each stage, (2) the composition of the data unit when it exits the stage, (3) the role and business unit responsible for that stage, (4) individual(s) that may assume this role, (5) the processing steps to complete that manufacturing step, (6) the business rules/constraints associated with it, (7) a description of the technology used at this stage, (8) and the physical location where the step is performed. These help the decision-maker understand what is the output from this step, how was this achieved including business rules and constraints applicable, where (both physical location and the system used), and who is responsible for this stage in the manufacture. The IPMAP shows when (at what stage) an operation was performed.

We illustrate how quality can be evaluated using the IPMAP one DQ dimension: accuracy. We treat accuracy to be a perceived measure that is dependent on the decision-maker. In certain situations, it is possible to evaluate accuracy in an objective manner. For instance, an objective measure of accuracy in databases might be computed as \[\text{Accuracy} = 1 - \frac{\# \text{ of data items in error}}{\text{Total } \# \text{ of data items}}\]. For individual data elements it could be computed as \[\text{Accuracy} = 1 - \frac{\{\text{Correct Value} - \text{Actual Value Used}\}}{\text{Correct Value}}\]. Here the actual value is known and is used in the assessment of error and computation of accuracy. In most decision-tasks, the actual value is unknown at the time of decision-making. The accuracy is determined using several other intangible factors including the decision-maker’s own experiences and intuition as well as the decision-maker’s perceived trust and confidence in the source from which the value for the data element is obtained. Further, how accurate a data element needs to be is also dependent on the decision task at hand.

The raw data units that come in from data source blocks are assigned an accuracy value by the provider or by the decision-maker. The value assigned is between 0 and 1, with 1 indicating a very accurate value for the corresponding data unit. Inspection blocks do not affect the accuracy of the data unit(s) that flows through these blocks. While inspection may improve completeness of the data, there is no evidence that it improves the original accuracy.
A processing block may combine raw and/or component data units to create a different component data unit. The accuracy of the output data element in a processing block is dependent on the processing performed and the determination of a functional formula to express accuracy of the output data element is a difficult problem. The formula proposed here is based on a generic process that combines together multiple data elements to create an output – a typical occurrence in sensory data aggregation. It does not take into account the type of processing performed and ignores the error (in accuracy) that might be introduced by the process itself. To compute the accuracy of the output data element from a processing block, the decision-maker may assign weights (continuous between 0 and 1) to each input of the processing block and the output accuracy is a weighted average of the accuracy of the inputs. For example, let there be n data elements flowing into one processing stage (say, x). Let Ai denote the specified (would be a computed value if it is a component data element) accuracy of raw data element i. Let us further state the decision-maker’s perceived accuracy of the data element i is ai. The accuracy of the output data element of stage x is:

\[
Ax = \frac{\sum_{i=1}^{n} (ai * Ai)}{\sum_{i=1}^{n} (Ai)}
\]  

(1)

In case of inspection and storage blocks, the accuracy of the output elements is the same as the accuracy of the corresponding input elements. For addition data elements introduced during the inspection, the inspector can assign new values for accuracy. Further, the decision-maker can attach a relevance factor \(\propto\) (between 0 and 1) to account for how sensitive accuracy is in the final quality evaluation of the data element at that stage. The absence of an objective measure can result in the custodian of some data element (say, k) inflating the specified accuracy (Ak) of that data element due to vested interests. The perceived accuracy ak of that data element that is assigned by the decision-maker allows the decision-maker to adjust for such biased values.

**Reachability in IPMAP** is the ability to identify all production stages of an IP that can be reached from a (any) given stage in the IPMAP. Reachability plays an important role in identifying impacts of quality errors. For example, if a data unit at some stage in the IPMAP is of poor quality it would affect all the stages in the manufacture of one or more information products that are “reachable” from this stage. **Traceability in the IPMAP** is defined as the ability to identify (trace) a sequence of one or more stages that precede any stage. This capability helps track data quality problems to its source (some intermediate stage or a data source) To implement these capabilities we first map the IPMAP onto its corresponding graph, IP-graph. The IP-graph is a directed graph. Given any IPMAP \(I\), it can now be represented as an IP-graph \(G(N, L)\). Each node \(n \in N\) represents a block in \(I\), and each link \(l \in L\) is defined by the ordered pair \((x, y)\) where \(x, y \in N\). This mapping process generates a mapping set \(P\). Each member of \(P\) is an ordered-pair \(<b, n>\) where \(b \in I, n \in G\).

**INFORMATION TECHNOLOGY ARCHITECTURE**

Sensory networks generate very large volumes of data. While some applications can manage streaming data, typical business applications require data to be stored for reasons such as data warehousing, mining, and knowledge creation. Prior to deploying a sensory network organizations must identify the data needs to be met by the network. To manage data quality in sensory networks the first step is to ensure that the right data and only that is delivered. In this section we examine some of the issues that help organizations deploy sensors and manage sensor data – issues that affect data relevance and data completeness.

Figure 2 presents a conceptual architecture for deploying sensors and sensory networks. The network architect must first identify the business needs of the organization, the data needs that satisfy each business need, the points in the domain (where the network is to be deployed) at which data is to be collected, the analytical environment for data analysis, and the processes to transform raw data to fit the analytical environment. The decision network layer 3 captures this information in the form of business rules, workflows, analytical structures, and metrics to track data how well the data satisfies business needs. This layer also defines the roles of users, the devices to be supported for the users, and the manner in which the devices can be used in the network. The data network layer contains the metadata to map the decision layer to the sensory layer. The network topology, sensor identification, database schemas to store the captured data, inter-relationships between the data

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3 Interdependencies exist between objects (e.g. business needs may share several workflows and/or business rules) within each layer and hence the term *network* layer. The same applies for the data layer.
elements, the types of users, their preferences for devices, and the functionality to support these devices in the network are included in the data layer. The sensory network layer is the physical deployment of the sensors. This layer must also define how users can seamlessly and transparently move between the different types of networks (802.11b, infrared, radio-frequency, and wired networks). This is critical as sensory networks do not exist by themselves but are typically part of larger information networks.

![Conceptual architecture for deploying sensory networks](image)

Even if the sensory network captures the right data, not all of the data elements are needed all the time. To implement this, filters are used to filter-out data that is not required at a certain time. It implies the capability to dynamically change the filter definition (what data should pass). Typically, filtering is performed after the data is captured in the database. Today sensors can be programmed remotely to read and transmit only the data that is necessary – in other words, filters are moved to the end of the network. This also implies that sensors transmit only necessary data and process out data that is not needed thereby managing their limited power more efficiently. The filter definitions would be part of the data layer in figure 2. How and when the filter definitions should change would be part of the decision layer in figure 2.

In this paper we have first examined the characteristics of sensory networks and their impact on data quality. We have then proposed a representation scheme for modeling sensory networks and shown how data quality along specific dimensions may be evaluated using the representation. We have also described a conceptual architecture to effectively deploy sensory networks – a fundamental issue that has a significant impact on data quality management in such networks. We have implemented a sensor network in a lab using MOTES. The simulated data from this network is used to evaluate the usefulness of a tool, the IPVIEW for managing data quality in real-time.

REFERENCES