Semantic middleware for industrial sensors

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ABSTRACT

For many years, plant engineers have used data collected from industrial sensors for supporting the diagnosis of failures. Recently, data scientists are using these data to make predictions on industrial processes. However, the meaning and the relationships of each specific sensor is unknown to people outside the engineering context. Conventional approaches to create a semantic layer for industrial sensors require a rigid “term alignment” followed by a lot of manual efforts. Hence, the problem is frequently set aside by industries. However, this condition limits the usage of advanced analytics tools in industries, preventing the capture of potential benefits. Since there are naming conventions and some other rules defined by engineers, this study takes these standards into account and analyze the metadata of sensors intending to automate the creation of a semantic middleware able to indicate the meaning of each sensor and its relationships with other sensors, equipments, areas, plants and other entities. This study intends to answer the following research question: Which approach could automate the creation of a semantic middleware for industrial sensors? In order to address the objectives of this study, we performed an empirical research using sensor metadata from three different plants from a mining company. As a result, we present MINDSense, a method that creates an ontology capable of describing the meaning of industrial sensors and its relationships. We conclude that this method contributes to leverage advanced analytics in industries and to increase the potential of new studies on top of industrial sensors data.

Keywords: Semantic Middleware. Ontology. Industrial sensors. Data Science.

Middleware semântico para sensores industriais

RESUMO

Por muitos anos, engenheiros de plantas têm usado dados coletados de sensores industriais para suportar o diagnóstico de falhas. Recentemente, cientistas de dados estão usando esses dados para fazer previsões em processos industriais. Contudo, o significado de cada sensor específico e suas relações é desconhecido para pessoas que não estão no contexto da engenharia. As abordagens convencionais para criar uma camada semântica para sensores industriais requerem rígido "alinhamento de termos" seguido de muitos esforços manuais. Por isso, o problema é frequentemente deixado de lado pelas indústrias. No entanto, esta condição limita o uso de ferramentas de analytics em indústrias, evitando a captura de benefícios potenciais. Uma vez que existem convenções de nomenclatura e outras regras definidas pelos engenheiros, este estudo leva esses padrões em consideração e analisa os metadados de sensores visando automatizar a criação de um middleware semântico capaz de indicar o significado de cada sensor e suas relações com outros sensores, equipamentos, áreas, plantas e outras entidades. Este estudo pretende responder à seguinte questão de pesquisa: Qual abordagem poderia automatizar a criação de um middleware semântico para sensores industriais? Para atender aos objetivos deste estudo, realizamos uma pesquisa empírica usando metadados de sensores de três plantas diferentes de uma empresa de mineração. Como resultado, apresenta-se o MINDSense, método que cria uma ontologia capaz de descrever o significado dos sensores industriais e seus relacionamentos. Conclui-se que este método contribui para alavancar análises avançadas nas indústrias e aumentar o potencial de novos estudos sobre dados de sensores industriais.

Palavras-chave*: Camada semântica. Ontologia. Sensores industriais. Ciência de dados*

Middleware semánticos para sensores industriales

RESUMEN

Durante años, los ingenieros utilizaron datos recolectados de sensores industriales para soportar el diagnóstico de fallas. Recientemente, los científicos de datos están utilizando estos datos para hacer previsiones en procesos industriales. El significado de cada sensor específico y sus relaciones son desconocidas para las personas que no están en el contexto de la ingeniería. Los enfoques convencionales para crear una semántica para sensores industriales requieren un rígido "alineamiento de términos" seguido de esfuerzos manuales. Por eso, el problema es dejado de lado por las industrias. Esta condición limita el uso de herramientas de análisis en las industrias, evitando la captura de beneficios potenciales. Una vez que existen convenciones de nomenclatura y otras reglas definidas por los ingenieros, este estudio lleva estos estándares en consideración y analiza los metadatos de sensores para automatizar la creación de un middleware semántico capaz de indicar el significado de cada sensor y sus relaciones con otros sensores, equipos, áreas, plantas y otras entidades. Este estudio pretende responder a la siguiente pregunta: ¿Qué enfoque podría automatizar la creación de un middleware semántico para sensores industriales? Para atender a los objetivos de este estudio, realizamos una investigación empírica usando metadatos de sensores de tres plantas diferentes de una empresa minera. Como resultado, presentamos el MINDSense, un método que crea una ontología capaz de describir el significado de los sensores industriales y sus relaciones. Concluimos que este método contribuye a aprovechar análisis avanzados en las industrias y aumentar el potencial de nuevos estudios sobre datos de sensores industriales.

Palabras clave*: Middleware semántico. Ontologia. Sensores industriales. Ciencia de datos*

INTRODUCTION

Companies are aware that the timely analysis and monitoring of business processes are essential to identify non–compliant situations and react immediately to those inconsistencies (VERA-BAQUERO; COLOMO-PALACIOS; MOLLOY, 2016). It is also known by companies that some studies that were difficult to conduct in the past due to lack of data can now be carried out. (LIU et al, 2016). Big Data and the mechanisms by which it is produced and disseminated introduce substantial changes in the ways information is generated and is made relevant for organizations. (CONSTANTIOU; KALLINIKOS, 2015).

Notably, industries are researching and implementing Big Data technologies intending to make their automation assets more reliable and predictive. The integration of IT systems with automation systems can become an essential tool for business users in the decision-making process. (VERA-BAQUERO; COLOMO-PALACIOS; MOLLOY, 2016). ICT technologies inside the engineering domain turn devices and equipment into intelligent systems, communicable and integrated from the field level to the operation level with a seamless data flow in both directions.

Nevertheless, even with all the progress that has been made, companies are still struggling with how to capture insights that are not obvious. It is a problem of how to discover meaningful relationships. (HURWITZ; KAUFMAN; BOWLES, 2015). For many years, plant engineers have used data collected from industrial sensors for supporting the diagnosis of failures. However, the meaning and the relationships of each specific sensor is unknown to people outside the engineering context.

Recently, data scientists are trying to use these data to make predictions on industrial processes. But, conventional approaches to create a semantic layer for industrial sensors require a rigid "term alignment" followed by a lot of manual efforts, not mentioning the difficulties to keep the semantic layer up-to-date. Hence, the problem is frequently set aside by industries. However, this condition limits the usage of advanced analytics tools in industries, preventing the capture of potential benefits. In this context, the following research question emerges: Which approach could automate the creation of a semantic middleware for industrial sensors?

Since there are naming conventions and some other rules defined by engineers, in this study we take these standards into account and propose MINDSense - an acronym for "Middleware for Industrial Sensors". MINDSense analyzes the metadata of sensors to automate the creation of a semantic middleware able to indicate the meaning of each sensor and its relationships with other sensors, equipments, areas, plants and other entities. MINDSense contributes to leverage advanced analytics in industries and to increase the potential of new studies on top of industrial sensors data.

This paper is structured as follows. An example of how the lack semantic prevents the development of an analytics layer on top of industrial sensor data is presented in section Running Example. In section Background, the academic foundation related to the main topic of this study is discussed. In section Methods, the details regarding the development of MINDSense are provided. The achievements reached with the usage of MINDSense are presented in Results section. Other approaches close to MINDSense approach are presented in section Related Work. The paper is concluded in the Conclusion section.

RUNNING EXAMPLE

A multi-plant industry usually has a centralized area for performing data science researches. However, sensors, typically counted on dozens per equipment, can be named in a different way in different plants. This happens because plant engineers can define a different naming convention for the sensors under his responsibility. Besides that, for several reasons, it is possible to exist naming deviations even inside a single plant. This way, to perform any study, data scientists strongly depend on plant engineers to understand the meaning of each specific sensor and its relationships.

Consider a scenario where a data scientist, examining patterns to create a predictive model, needs the full list of sensors that monitor a given equipment that in turn, is used across multiple plants. In this case, this data scientist would need to talk to several plant engineers while manually conceiving his list. The lack of term alignment between those involved hinders the process, creating an environment that is subjective and susceptible to errors. Now, suppose a new sensor is deployed on a plant after the data scientist gathered all information? The process should be restarted. Thus, the lack of semantic for industrial sensors slows down the process of development of analytics.

BACKGROUND

Most real-world data are not in a form that can be directly recorded by a computer. These quantities typically include temperature, pressure, distance, velocity, mass, and energy output (such as optical, acoustic, and electrical energy). A physical quantity must first be converted to an electrical quantity (voltage, current, or resistance) using a sensor or transducer. (AUSTERLITZ, 2003). Thus, transducers and sensors are used to convert a physical phenomenon into an electrical signal (voltage or current) that will be then converted into a digital signal used for the next stage such as a computer, digital system, or memory board. (EMILIO, 2013).

At the highest level, a sensor is something that, when stimulated, detects some aspect of physical phenomena (called input). By way of a transducer, the sensor turns the measurement into a signal so it can be electronically processed and then measured or recorded as output. (STIMMEL, 2015). Devices with input function are called sensors because they detect a physical event that changes according to some events as, for example, heat or force. Instead, device with output function are called actuators and are used in control system to monitor and compare the value of external devices. (EMILIO, 2013). The output is used as input to a further system or process that triggers some responsive action. This is called actuation and may require yet another transducer to convert the output to yet another signal type. (STIMMEL, 2015).

Sensors can monitor the physical world by detecting and measuring different types of environmental information. By feeding suitable applications with such type of information via various types of physical world objects, the Internet would move from "interconnected computers" to "interconnected things." (CHAQFEH; MOHAMED, 2012). Sensor types include: temperature sensors, magnetic field sensors, potentiometers, light detection sensors, among others. (EMILIO, 2013). Table 1 gives more details about sensors and transducers.

SEMANTIC MIDDLEWARE

The development of tiny sensors and actuators can realize intelligent context-aware networking in large factory environments, automotive networks, smart homes and offices, and social services support including earthquake warnings, patient monitoring and context-aware support in emergency situations. (CHAQFEH; MOHAMED, 2012).

A Middleware platform for the IoT provides an abstract layer interposed between the IT infrastructure and the applications. It aims to hide the technological details to enable the application developers to focus on the development of the IoT applications. (CHAQFEH; MOHAMED, 2012). When billions of sensors are connected to the Internet, it is not feasible for people to process all the data collected by those sensors. Context-awareness computing techniques, such as IoT middleware are proposed to better understand sensor data and help decide what data needs to be processed. (XU; HE; LI, 2014).

Besides describing all IoT infrastructure, a semantic middleware platform explains the meaning of each existing device for any application or consumer. The general idea is that semantic middleware is able to automatically discover and store metadata about IoT devices. IoT middleware may have several features, such as described in table 2.

Table 1 – Type of sensors

Sensor Type	Description
Temperature sensors	Contain electrical parameters that vary with temperature, following well-characterized transfer functions
Optical sensors	Used for detecting light intensity. Typically, they respond only to particular wavelengths or spectral bands.
Force and Pressure Transducers	A wide range of sensors are used for measuring force and pressure. Most pressure transducers rely on the movement of a diaphragm mounted across a pressure differential.
Magnetic Field Sensors	Used to measure either varying or fixed magnetic fields.
Ionizing Radiation Sensors	Can be particles produced by radioactive decay, such as alpha or beta radiation, or high-energy electromagnetic radiation, including gamma and X-rays. In many of these detectors, a radiation particle (a photon) collides with an active surface material and produces charged particles, ions, and electrons, which are then collected and counted as pulses (or events) per second or measured as an average current.
Position (Displacement) Sensors	A wide variety of transducers are used to measure mechanical displacement or the position of an object. Some require actual contact with the measured object; others do not.
Humidity Sensors	Relative humidity is the moisture content of the air compared to air completely saturated with moisture and is expressed as a percentage.
Fluid Flow Sensors	Many industrial processes use fluids and need to measure and control their flow in a system. A wide range of transducers and techniques are commonly used to measure fluid flow rates (expressed as volume per unit time passing a point).
Fiber Optic Sensors	Used to measure a wide range of quantities, including temperature, pressure, strain, displacement, vibration, and magnetic field, as well as sensing chemical and biomedical materials. They are immune from electromagnetic interference (EMI), can operate in extremely harsh environments, can be very small, and are fairly sensitive

Source: Based on Austerlitz (2003)

Table 2 – Features of a semantic middleware

Feature	Description
Interoperation	Interoperation shares information and uses the same across diverse domains of applications using diverse communication interfaces
Context detection	Context is responsible for characterizing the situation of an entity where an entity can be person, place, or object relevant to the interaction between a user and an application, including the user and applications themselves.
Security	Security and privacy are responsible for confidentiality, authenticity, and nonrepudiation.
Portability	Managing data volumes is an integral part of IoT-middleware. It is believed that there will be trillions of objects which will be part of this enormous network and hundreds of Exabytes will be stored or exchanged among the objects
Device discovery	Device discovery and management enables any device in the IoT network to detect all its neighbouring devices and make its presence known to each neighbour in the network. Device ontology is used for storing information about the heterogeneous devices.

Source: based on Bandyopadhyay et al. (2011).

INDUSTRIAL SENSORS

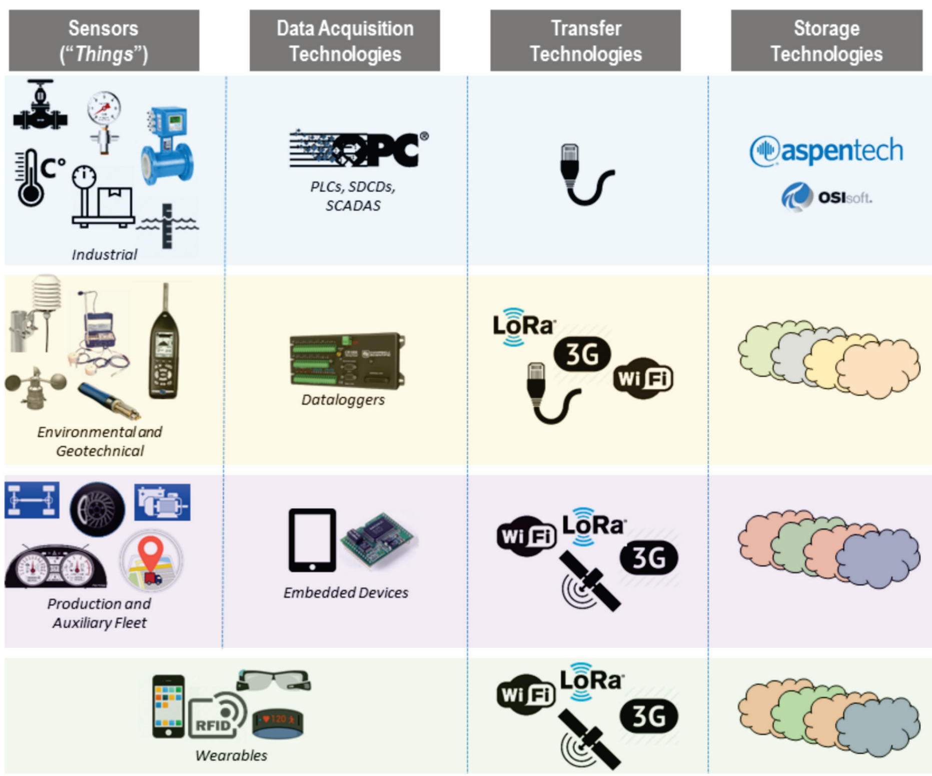
This study considers a middleware capable of describing the semantic for industrial sensors. Information Technology (IT) has been an enabling and driving force practically in all engineering domains including automation. Today, all subsystems of an automation system, from field level to operation level, has become IT enabled and driven. (SHARMA, 2017). While the term "Internet of Things" or IoT is relatively a new concept for connecting things, the basic idea of IoT is to connect all physical devices to collect their relevant data in real time to manage the "things" better and make "things" more reliable and predictive. (GUNASEKARAN et al, 2017).

Collecting data from industrial sensors is nothing new for industries. In a general way, data from industrial sensors are collected by programmable logic controllers (PLCs). Data from environmental and geotechnical sensors are usually collected by datalogger devices, positioned close to sensors.

Data from production and auxiliary fleet are retrieved by embedded devices, placed inside the fleet. Data from industrial wearables are collected from different ways. In the industrial environment, all data are routed to a supervisory software, used by operators to analyze data and make real-time plant-floor decisions. On top of this architecture, a time-series data historian system is frequently included with capabilities to store data from multiple sensors.

Softwares such as InfoPlus.21 (by AspenTech), PI System (by OSISoft) among others, are used with this purpose. This kind of software is an industrial version of a key-value-pair (KVP) database, with specialized functions such as: data compression, ad-hoc calculations, statistics, among others. Figure 1 shows how data is collected from sensors in industrial environment.

Figure 1 – How data are collected in industrial environments



Source: Authors

However, it is difficult to identify characteristics of a specific sensor for those who are outside the engineering context, as they are not familiar to naming conventions adopted by each specific plant. This study focuses on industries with naming conventions for sensors, even when there are different versions for each plant. It is proposed an IoT middleware as an approach to deliver semantic for industrial sensors, automatically created based on naming conventions.

METHODS

The general idea of our approach is depicted in Figure 2. MINDSense (Middleware for Industrial Sensors) was designed to be accessible as an independent service and acts as an information provider not only about sensors and actuators but also on the existing relationship between machinery and sensors. Thus, analytics applications may acquire the necessary metadata to locate and interpret sensor readings while data scientists may use it as a common knowledge repository on the topic. Queries are made using the SPARQL language (Version 1.1), carried through the HTTP protocol in a REST API, while responses are encoded as JSON/XML messages. These architectural decisions aim to facilitate the system interoperability, particularly with legacy applications. The SPARQL engine interprets such queries seeking data on our ontology model stored in a triple database engine.

We have built MINDSense on top of Apache Jena[1], an open source Java framework for building semantic web applications. To express the knowledge we selected the OWL language, in the OWL DL profile which renders the maximum expressiveness possible while holding completeness and decidability, common prerequisites for descriptive logic based reasoners.

Sensor metadata collected in this study is derived from the naming patterns employed by three different port plants of a Brazilian mining company. A domain specialist yielded the necessary consulting during the process and was responsible for generating the initial data set from the company's internal database infrastructure (made available in CSV files). The data were extracted from Aspentech InfoPlus.21 database through a SQLPlus query specifically created for the purpose of this study. This preliminary data structure was used to feed MINDSense. The dataset is comprised of 42,583 rows where each row determines a sensor. Table 3 provides a sample of our data.

Table 3 − Sample of sensor metadata

Sensor tag	Description	IO Type	Unit
1GR04A_DV_HOR_01_D	Hourmeter of equipment 1GR04A	Analog	Hour
1PA0_M1_POT_01_D	Potentiometer for equipment 1PA0	Analog	Kilowatts
1GR04A_DV_DIAG_01_D	Diagnostic word	Discrete	--
EP03_LAN_ELEV_01_D	Current position - Elevation	Discrete	Millimeters

Source: Author

[1] Available at https://jena.apache.org/index.html

The naming conventions applied in column 'Sensor tag' is particularly relevant as it implicitly wraps at least six sensor characteristics. Splitting its value at the character 'underline' reveals the Equipment and Sub-Equipment a sensor monitors, its purpose, sequence and data source, respectively. The sensor tag at the first row, for instance, indicates that there is a sensor (1GR04A_DV_HOR_01_D) that monitors a piece of sub-equipment (DV) of a piece of equipment (1GR04A). It is a sensor read directly from an automation system (D) which indicates an hourmeter, that is, the amount of time the device is running (HOR) - the type of sensor is related to Table 1. It also informs that this sensor is the first of its type installed on the device (01). Metadata such as database connection, Port plant, organizational area and its corresponding labels, although available for processing, have been omitted from the table.

These naming patterns, though, are not strictly consistent throughout the organization. Considering our sample, a significative number of sensors (13,647 or 32.04% of the total) contained incomplete data or unstandardized values. Under these circumstances, the ability to make inferences on incomplete information while enabling structural revisions, data correction, and posterior knowledge enrichment are considered "must have" features what, on the other hand, poses modeling challenges for applications based on traditional relational databases. In this sense, the MINDSense approach takes advantage of the open-world assumption (OWA) typically made by semantic web languages such as the OWL language. The OWA states that no inferences can be drawn from statements that haven't been made yet, what enables the work with incomplete information. To illustrate this concept, consider the following axiom: "Sensor X is a sensor of equipment Y". If we enquire a typical RDBMS with "Is sensor X a sensor of equipment Z?", the answer is "No". The same question, nevertheless, would render a different answer when submitted to an OWA based system: "Unknown".

RESULTS

Considering the common features of a semantic middleware, such as those mentioned in Table 2, the product generated in this study is interoperable, has context detection capabilities and enables device discovery. The simplified version of the ontology created for MINDSense is described in more details in Figure 3 that follows the notation produced by WebVOWL. (LOHMANN et al, 2014). The class "Sensor", as expected, is a key element in MINDSense ontology and its individuals are associated to one of its subclasses according to its purpose (defect, elevation, status, and so on).

Sensors are responsible for monitoring Machines (instruments designed to transmit or modify the application of power, force or motion) that must be classified as an instance of equipment or sub-equipment. Equipment refers to machines that are directly controlled by a mining plant during the extraction or transport activities. Sub-equipment is a machine that acts as part of an instance of equipment. In this context, a crane is a piece of equipment while its oil pump is an instance of sub-equipment. Machines and Sensors are Spatial Things that, in turn, are allocated at places such as an areas and plants.

The application of the ontology in our sensors sample resulted in 19 classes, 516,859 axioms, 516,824 logical axioms, 28 declaration axioms, 9 object properties, 6 data type properties and 56,565 individuals.

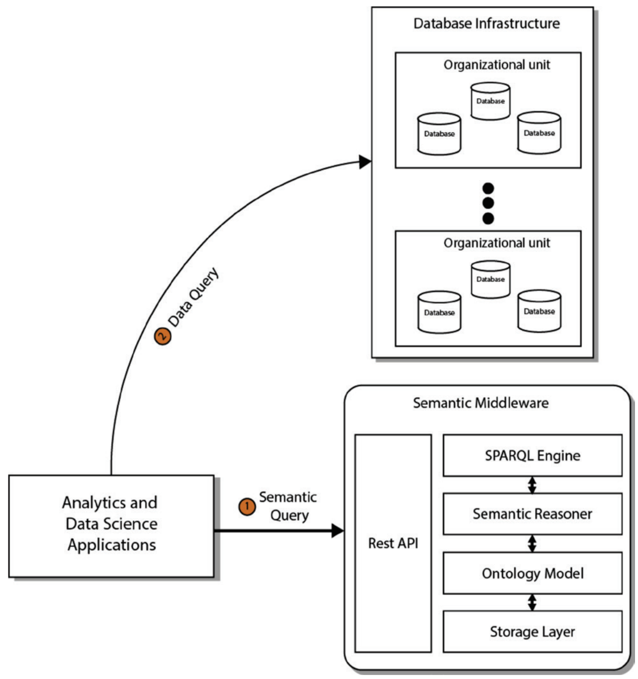
MINDSense[2] allowed stakeholders from outside the engineering context - including data scientists - to interact with meta data from industrial sensors, obtaining information that, until then, was restricted to domain experts of each organizational unit. The middleware usage is also useful for inducing storage standardization and term-alignment across the organization. These factors contribute to leverage advanced analytics in industries what, in turn, increases the potential of new findings on top of industrial sensors data.

[2] The source code of our semantic middleware is publicly available at http://github.com/dfalci/semanticmiddleware

Table 4 exemplifies some questions that MINDSense is naturally able to address. These questions are directly related to running example mentioned in the beginning of this paper.

MINDSense fulfills an existing lack in industrial plants as they do not have an automated data model capable of representing physical structures and relationships among industrial equipments. Our middleware also presents relationships between sensors and equipments despite the volume of industrial sensor data collected. Another advantage is that it creates a flexible model that could answer the requirements of each data consumer while creating a standardized model that could be shared across the enterprise. Depending on consumer requirements, different SPARQL queries could be written, answering specific questions but keeping the main data structure.

Figure 2 − MINDSense: a semantic middleware for industrial sensors



Source: Authors

Table 4 − Common questions and its SPARQL translations to MINDSense

Question	SPARQL query

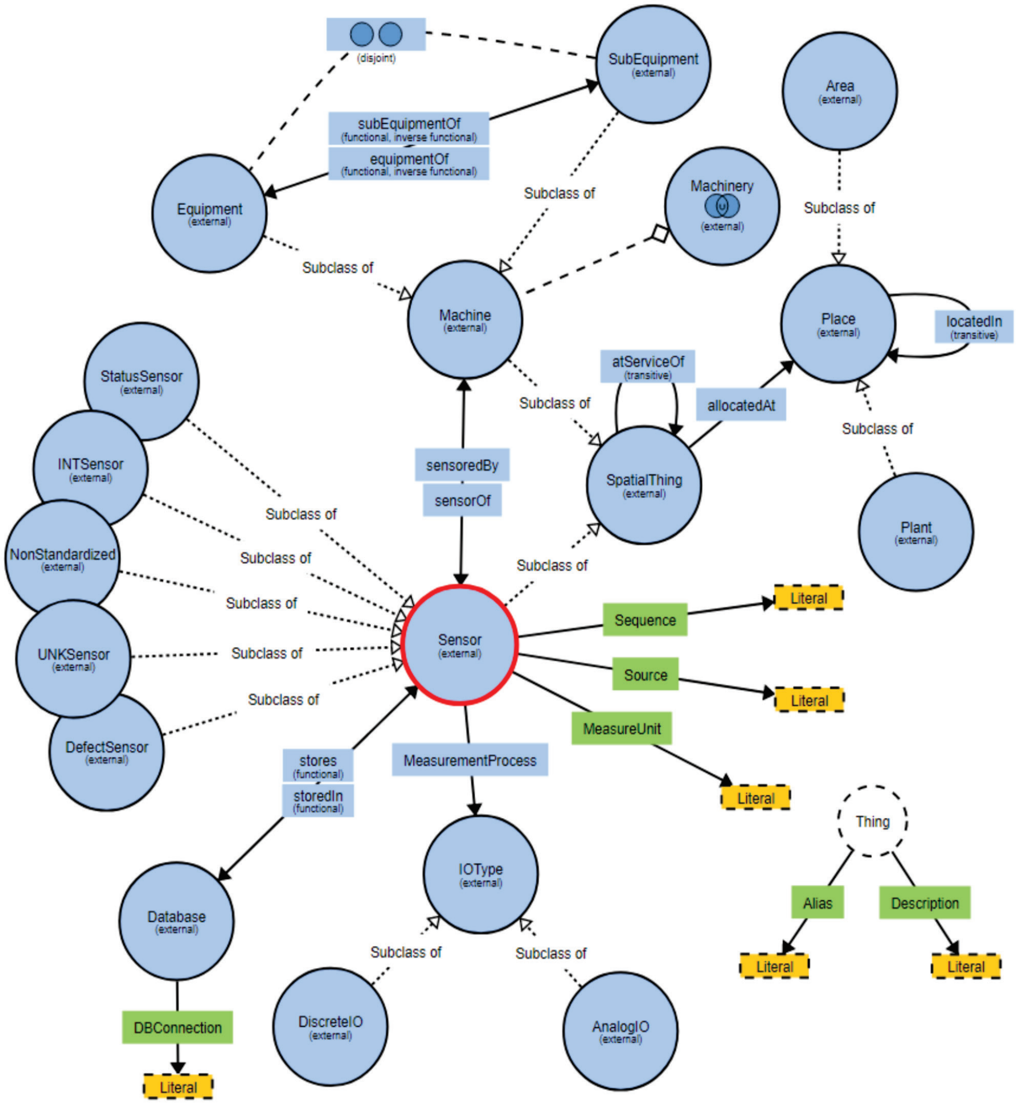
In what databases one can find sensor readings from the sensor S?	SELECT ?db {
	?x rdf:type/rdfs:subClassOf* sm:Sensor;
	sm:storedIn ?db.
	FILTER (?x = <sensor>)
	}

What are the sensors of equipment Z?	SELECT * WHERE {
	?x sm:atServiceOf+ <equipment>.
	?x rdf:type/rdfs:subClassOf* sm:Sensor.
	}

What are the name of the defect sensors of equipment Z across different port plants?	SELECT ?alias ?port WHERE {
	{ SELECT ?d WHERE {
	?d a sm:Equipment.
	Filter(?d = <equipment>)
	} }
	?a rdf:type/rdfs:subClassOf* sm:DefectSensor;
	sm:Alias ?alias;
	sm:allocatedAt ?port;
	sm:atServiceOf ?t.
	FILTER (?t = ?d)
	}

Source: Authors

Figure 3 − Concepts and Relations of MINDSense Ontology



Source: Authors

RELATED WORK

This study is strongly related to Soignier (2017), as the author proposed a graph-based data model for industrial sensors data. The author references a product called ElementGraph which can be coupled to OsiSoft PI System. The main contribution of MINDSense is being able to implement a similar proposition capable of interacting with any industrial sensor database, including InfoPlus.21.

Diego, Martinez, Rodriguez-Molina, Cuerva (2014) and Maffei (2017) propose a semantic middleware for energy grid. The first approach considers features such as device discovery and context detection. The second approach includes those features and adds interoperation and portability features. Additionally, those studies consider specialized functions for the middleware like energy analysis and demand forecasting. Our work differs from theirs because we considered all applications, conceptually dissociated from the middleware layer, creating a more generic semantic middleware.

CONCLUSION

In this study, we presented MINDSense as a method that dynamically creates an ontology describing the meaning of industrial sensors and its relationships. We firstly presented the lack of semantics for industrial sensors as a problem to be solved. Then, we stated that the ability to work, making inferences on incomplete information, enabling revision, correction, and posterior knowledge enrichment are considered "must have" features, which poses modeling challenges for applications based on traditional relational databases. Next, we described MINDSense as a semantic middleware that could be accessible as an independent service and act as an information provider not only about sensors and actuators but also on the existing relationship between machinery and sensors.

MINDSense made possible to directly answer questions that were restricted to domain experts of each organizational unit and this contributes to leverage advanced analytics in industries and to increase the potential of new studies on top of industrial sensors data.

As a future work, our approach could be improved to include features such as security and portability. Considering we used open software tools, MINDSense can be modified by third party developers and further expanded. Also, other studies could implement our model in a real scenario, allowing the interaction of analytics tools with sensor data in real time.

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