The sensor to decision chain in crisis management

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ABSTRACT

In every disaster and crisis, incident time is the enemy, and getting accurate information about the scope, extent, and impact of the disaster is critical to creating and orchestrating an effective disaster response and recovery effort. Decision Support Systems (DSSs) for disaster and crisis situations need to solve the problem of facilitating the broad variety of sensors available today. This includes the research domain of the Internet of Things (IoT) and data coming from social media. All this data needs to be aggregated and fused, the semantics of the data needs to be understood and the results must be presented to the decision makers in an accessible way. Furthermore, the interaction and integration with existing risk and crisis management systems are necessary for a better analysis of the situation and faster reaction times. This paper provides an insight into the sensor to decision chain and proposes solutions and technologies for each step.

Keywords

Sensors, Internet of Things, Ontology, Knowledge Base, Ontology Visualization, Decision Support, Early Warning

INTRODUCTION

Recent research from the World Meteorological Organisation showed that the global temperature increase caused by climate change could reach 3°C by the end of the century (World Meteorological Organisation, 2017). As a consequence, the probability for the occurrence of natural catastrophes like heat waves, floods and forest fires is rising. The United Nations have long been calling for the intensified worldwide development of early warning systems (UNISDR, 2005). In the 2015 resolution “The Sendai Framework for Disaster Risk Reduction 2015-2030" this requirement was extended to include the consideration of chained disasters (UNISDR, 2015). Thus, the authorities of potentially affected regions need to prepare themselves. Early warning, risk and crisis management systems can provide these authorities with the necessary methods for decision support.

In this context, we developed and are presenting in this paper a general method to facilitate decision support by data integration via sensors and semantic data analysis, which can form the basis and integration framework of such systems: the sensor to decision chain in crisis management. The goal of the chain is to provide decision support functionality for responsible decision makers using a DSS.

The following sections of this paper will explain the sensor to decision chain. Since not all aspects can be covered in this paper, the focus lies on the harmonized sensor data collection, the semantic modelling of the multiple domains (climate change, crisis management, data analysis) and the decision support. In the rest of the paper, section "Related Work" discusses existing decision support workflows. The next section introduces "beAWARE", the project in which the decision chain is developed and tested with three large scale use case studies. Section "Sensor Data and Access to Sensor Data" explains the Open Geospatial Consortium (OGC) SensorThings API[1] and gives examples how it is integrated in the beAWARE demonstrator. Section "Semantics" explains methods for storing and accessing the data in the Knowledge Base (KB) and provides examples based on the beAWARE ontology. Section "Data Analysis and Decision support" explains ideas for the fusion of the data and how the information from the data is derived, and, finally, section "Conclusions and Future Work" recapitulates our findings and discusses directions for future developments.

RELATED WORK

Sprague defined DSSs through a group of properties, where one of the key characteristics is the support of decision makers in specific questions (Sprague, 1980). The goal of our sensor to decision chain lies exactly in providing this support.

In the meantime, DSSs did undergo a big development. Newman et al. describe in their current survey of "decision support systems for natural hazard risk reduction" (NHRR-DSS) the status and future research directions (Newman et al., 2017). They introduce a classification system for NHRR-DSS and found that most of the relevant systems considered single hazard situations. This shortcoming is addressed by the sensor and semantic components in our proposed solution, which enable the system to integrate multiple data sources.

A good overview over current architectural design and technologies of early warning systems is provided by Moßgraber (Moßgraber, 2017). These systems are supposed to deliver information about an emerging threat in order to allow persons and organizations to react accordingly. However, the design of an early warning system presents complex challenges to the system architects. In order to propose a solution to alleviate this problem, the presented work provides a framework for the architecture of next generation early warning systems. Particular attention is paid to solve various architectural problems by means of semantic technologies and the automation of workflows.

Another DSS combining current technical possibilities is introduced by Fang et al. in "An Integrated System for Regional Environmental Monitoring and Management Based on the Internet of Things" (Fang et al., 2014). The system combines IoT, Cloud computing and GIS technologies into an information system for environmental monitoring. Fang points out that research for data acquisition and fusion is important. Thus, as in the sensor to decision chain, Fang's proposed system architecture reflects the integration of sensors in the Perception layer, foresees services in the Middleware layer, and introduces decision support in the Application layer, but semantic integration is not considered.

Semantic integration is discussed in other recent works. Ontologies (Fensel, 2001) have been used for several purposes in DSSs. Wanner et al. present an "ontology-structured knowledge base from which then information relevant to the specific user is deduced and communicated in the language of their preference" (Wanner et al, 2014), while Moßgraber et al. use the ontology for improving the understanding of the use case domain, for visualizing the relations between the stakeholders and for structuring the information of the current situation (Moßgraber et al, 2015).

Decision Support for crisis management is discussed by di Pietro et al. (di Pietro et al., 2017). The introduced DSS manages critical infrastructures vulnerable in case of natural disasters. They structure the DSS architecture along the main functional blocks "Monitoring of functional phenomena", "Prediction of Natural Events", "Prediction of Damage Scenarios", "Prediction of Impact and Consequences" and "Support of efficient Strategies".

[1] https://github.com/opengeospatial/sensorthings

As in the work by Fang et al., semantic integration is not considered to improve the cross-domain integration of multiple data sources and risk domains.

THE BEAWARE PROJECT

The main goal of beAWARE[2] (Enhancing decision support and management services in extreme weather climate events) is to provide support in all the phases of an emergency incident. More specifically, it proposes an integrated solution to support forecasting, early warnings, transmission and routing of the emergency data, aggregated analysis of multimodal data and management of the coordination between the first responders and the authorities. It relies on platforms, theories, and methodologies that are already used for disaster forecasting and management and adds the elements that are necessary to make them work efficiently under the same objective.

The overall context for beAWARE lies in the domain of situational awareness and command and control. The first phase concerns the forecast of the extreme condition and the relevant preparations. Once a disaster occurs, an initial assessment needs to be conducted as soon as possible to determine the scope, geographical distribution, and scale of the incident. Situational awareness refers to being able to accurately determine what has happened, what is happening now, and what will come next, all in order to plan and coordinate the most effective response possible with the resources available. This observation phase will lead to an orientation phase suggesting both an individual as well as collective "cognition" orientation to data that is sensed and communicated. Once orientation to the data (or the lack of it) occurs, then a decision is made, ultimately resulting in the final step, which is "act". The crisis management center is always struggling to acquire a complete overview of the situation and to make the "best possible" decisions given the severe circumstances.

The proposed sensor to decision chain for crisis management is applied as the backbone of the architecture of a cross-domain crisis management system. Therefore, the key challenge of the project is to collect heterogeneous data from several resources, such as environmental, social media, input from first responders and/or people in danger, and to semantically integrate them in order to provide decision support services to the crisis management center.

Pilot Use Cases and Sensor Data

The beAWARE pilots cover different types of extreme weather events and, thus, employ different types of sensors, representing the *Sensor* part of our sensor to decision chain.

Flood Pilot

The most relevant sensors for the flood pilot are the water-level sensors in the different rivers in the pilot area, and the weather stations recording precipitation, since they reflect the current situation. The Finnish Meteorological Institute (FMI) makes forecasts of the weather, and the Italian Alto Adriatico Water Authority (AWAA) makes forecasts of the water-levels in the different rivers in the pilot area. The models used to create these forecasts can be seen as virtual sensors. Furthermore, first responders and the general public can send messages (including images and video) to the beAWARE system. However, the system cannot directly use this data once it arrives, as it has to be analyzed first by the respective analysis components.

Fire Pilot

An important indicator for fire-risk is the current and predicted weather. Important sensor data for this pilot are therefore data from weather stations and the weather forecast. High temperature, combined with low humidity and little precipitation increases the risk of fire. Regarding the detection of fires actually taking place, the most efficient way is by using static cameras that constantly record the area of interest and analyze the data from those cameras (near real-time) using video analysis software. Finally, the messages, images and videos sent by first responders and the general public are handled the same way as in the Flood Pilot.

Heatwave Pilot

Also for the Heatwave Pilot, the weather situation and the weather forecast are important sensor inputs, the same as for the other two pilots. Whereas for the Fire Pilot a low humidity increases the risk of fire, for the heatwave pilot a high humidity increases the severity of a heatwave. The messages, images and videos sent by first re-

[2] http://beaware-project.eu/

sponders and the general public are also handled the same way as in the previous two pilots. Finally, another relevant type of information is the location of shelters and how much space is still available in a specific shelter.

THE SENSOR TO DECISION CHAIN

As already motivated above, an integrated DSS needs to solve the problem of facilitating the broad variety of sensors available today. They can be accessed via Internet of Things (IoT) or Machine-2-Machine (M2M) standards. Furthermore, data coming from social media (human sensors) needs to be collected and analyzed, for example to get a better understanding of a crisis situation and to find people in need of rescue.

In this context, the key contribution of the paper is a proposed general method for facilitating decision support by data integration via sensors and semantic data analysis, which can constitute the foundation for crisis management DSSs. We call the chain of steps from retrieving sensor readings to reaching decision support as "the sensor to decision chain" in crisis management (see Figure 1).

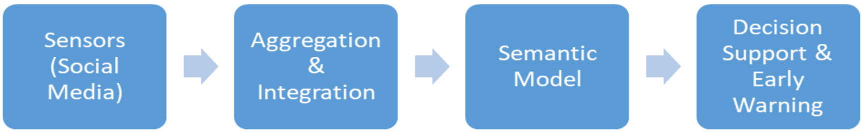

Figure 1: The sensor to decision chain

For integrating and harmonizing the data and for creating a common basis for further analysis, the Open Geospatial Consortium (OGC) developed a data model and API called the SensorThings API (Liang et al., 2016), which is further described in the following subsection.

All this data needs to be aggregated and fused, the semantics of the data needs to be understood and the results must be presented to the decision makers. To create a knowledge base (KB) that will assist in the decision support process, first an ontology needs to be created which semantically integrates the different pertinent domains like the sensor metadata, climate change, crisis management, etc. Once the KB schema is established, analysis services provided by the various components of the system can populate the KB with the respective analyses results. For example, a video analysis algorithm may detect that a street is flooded with several drowning cars. An instance of a corresponding incident is created in the KB, which is linked to vulnerable objects, in that case the cars. Based on that, the system can now generate automated suggestions to the decision maker; e.g. in the specific example, to check for people who might get trapped in a car. More information on these aspects is given later in the paper.

Stakeholder Access to Sensor to Decision Chain

In each pilot different types of stakeholder needs to access the Sensor to Decision Chain. Stakeholders providing data like FMI or AWAA will use the means of the Sensor Things API. People in danger or First Responders are also data sources for the DSS. They may access the chain directly via a mobile app, which will support means for the integration of their information into the Semantic Model. Additionally data provided through common Social Media (e.g. Twitter) will be crawled and included into the chain. The results of the Sensor to Decision Chain will be presented for two types of Stakeholder groups: firstly decision makers, which will get access via a desktop application and secondly the general public via a mobile app.

OGC SENSORTHINGS API

The OGC SensorThings API (Liang, 2016) is a REST interface and a data model for exchanging sensor data and metadata. The data model (see Figure 2) is based on the OGC/ISO Observations and Measurements model (OGC, 2011), but simplified to make it more suitable for use in the Internet of Things domain. It describes the eight entity types that can be accessed through the REST interface, and the relations between those entity types. The REST interface is based on the OASIS OData standard and allows Create, Read, Update and Delete actions on all entities (OASIS, 2014). It also offers powerful search capabilities, including geospatial and temporal filtering. Besides the REST interface, the OGC SensorThings API offers a Message Queue Telemetry Transport (MQTT) extension that allows for push notifications when entities change.

The data model of the OGC SensorThings API consists of the following eight entities:

- Thing: A virtual or physical object. Depending on the use case this can be the object being observed, such as a river or river section, or the sensor platform, such as a weather station.

- Location: The locations of Things. These can be geographic locations, encoded as points or areas, or symbolic locations, like "Crossing of road X and street Y".
- HistoricalLocation: the link between a Thing and a Location, with the time indicating when the Thing was in a certain Location.
- Sensor: The metadata of the sensor that generates data. This could be a real sensor, or mathematical model generating a prediction.
- ObservedProperty: A property of the feature of interest that is being observed by a sensor. For instance, the water level in a river.
- Datastream: a collection of Observations of one ObservedProperty, made by one Sensor, and linked to one Thing.
- Observation: a measurement made by a Sensor.
- FeatureOfInterest: The geographic area or location for which an Observation was made. This can be the same as the Location of the Thing, which is often the case for in-situ sensing. In the case of remote sensing, the feature of interest can be different from the location of the Thing, depending on what is chosen as the Thing. The feature is a geographical point or a polygon encompassing an area or volume, usually encoded in GeoJSON.

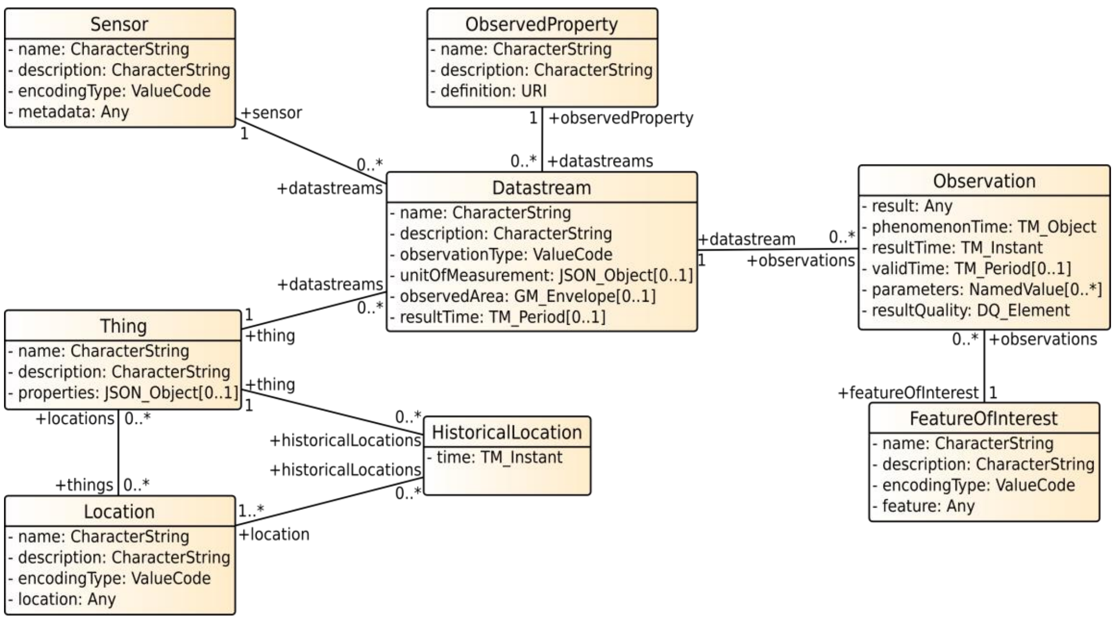

Figure 2: The OGC SensorThings API data model

The relations between these entities are also defined by the data model and most of them are one-to-many.

The relations of Location are a bit more involved: A thing can have zero or more Locations, but these Locations must all be different representations of the same physical location. For instance, one geospatial location represented by GPS coordinates, and one symbolic location. A Location can have zero or more Things.

Each time a Thing is linked to a new Location (or set of Locations) a new HistoricalLocation is generated that tracks the time when the Thing was at this Location. A HistoricalLocation also has the restriction that if it has more than one Location, these Locations have to be different representations of the same real-world location.

An important feature of the OGC SensorThings API is that it is possible to request data from related entities in a single query. For example, one can, in a single request, fetch a set of Things, with the Datastreams belonging to those Things, and for those Datastreams the ObservedProperty, and the last Observation. This makes it very easy to write data visualisation tools, since it is possible to fetch all relevant data in one request, instead of having to make many separate, asynchronous requests.

One of the first implementations of the OGC SensorThings API is made by Fraunhofer IOSB (van der Schaaf, 2016). This implementation is open-source, using the LGPL license. The current version offers a complete implementation of the standard, and all extensions, except for the batch-processing extension. It is written as a Java web-application and uses the PostgreSQL database system for data storage. This implementation has been used to include the meteorological data like temperature und rainfall and the water level data into the demonstrators of the pilots. It represents the second process step, the *Integration*, of the sensor to decision chain.

SEMANTICS

This section represents the *Semantic Model* step of our sensor to decision chain. The aim of the beAWARE ontology is twofold: (a) to represent natural disasters, along with the associated conditions and climate parameters characterizing them, and, (b) to represent the analysis results of input items (image, video, text) fed from sensors to the various beAWARE analysis components. Part of the ontology's design is inspired by existing models for representing similar notions:

- *MOAC* (*Management of a Crisis*) (Ortmann et al., 2011) constituted the basis of our representation for disaster impacts;
- The ontologies from the *SoKNOS* project (*Service-Oriented Architectures Supporting Networks of Public Security*) (Babitski et al., 2011) assisted us in the categorization of damages and resources;
- The scheme for representing environmental and meteorological conditions is based to some extent on the *PESCaDO* ontologies (Rospocher & Serafini, 2012).

Representing Natural Disasters

Figure 3 illustrates how the beAWARE ontology covers point (a) above, namely, representing natural disasters. Class "*Natural Disaster Type*" represents the various types of disasters, like e.g. floods, forest fires, storms or earthquakes etc. Disasters may lead to other disasters (via property "*leads to*"); for instance, a heat wave may lead to fires, or storms may lead to floods. Each type of disaster is characterized by certain climate parameters, represented via class "*Parameter*"; for example, solar radiation and temperature are two parameters that characterize a heat wave.

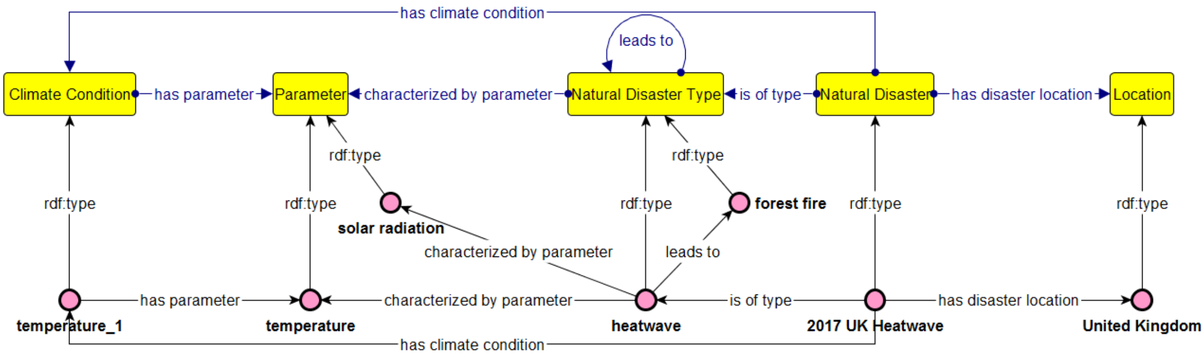

Figure 3: Representing natural disasters in the beAWARE ontology.

As seen in the figure, the actual manifestation of a natural disaster is represented via class "*Natural Disaster*", an instance of which (e.g. a heat wave in the city of Thessaloniki during the summer of 2015) has specific climate conditions with specific values.

Representing Analyzed Data

The array of beAWARE sensors submit the input data to the beAWARE analysis components, the analysis results of which are then fed to the ontology and are represented as displayed in Figure 4. These constructs facilitate representing the notions from point (b) above.

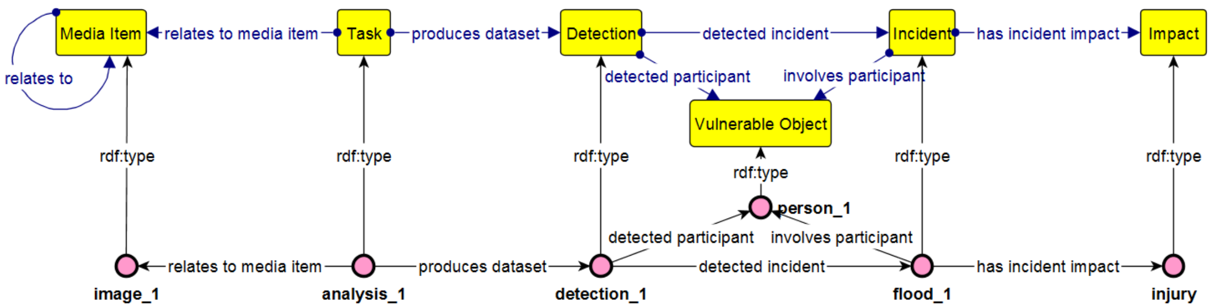

Figure 4: Representing analyzed data in the beAWARE ontology.

Class "*Media Item*" represents an item of analyzed data, which is related to some analysis task (via class "*Task*"). The analysis (text analysis, image analysis or video analysis) produces a "*Detection*" dataset containing all relevant information (e.g. an object detection task may produce a dataset of detected incidents, objects, and confidence scores). For reasons of brevity, we have not included in the figure the complete typology (i.e. hierarchy) of vulnerable objects (e.g. assets, persons, infrastructure, buildings etc.), impacts and incidents. For the same reasons, we are not displaying various data type properties, like e.g. severity levels, confidence scores, detection timestamps etc.). Moreover, the figure also demonstrates an example of a video analysis instance, where a potentially injured person is detected in the flood.

ONTOLOGY VISUALIZATION

Visualizations of the ontology play an important role in helping an end user to understand the model's inherent structure, so that he can efficiently work with the ontology. Thus we integrated means for visualizing the above described ontology into the DSS to facilitate the access to the semantic model for decision making stakeholders. When a user is viewing a specific instance or concept, he has to be given an overview of the relations to other instances and concepts that this instance or concept has. Furthermore, which relations to display can differ from case to case, and often it is not sufficient to simply show all primary relations of the instance or concept. Often it can be very helpful to display the instance or concept in a specific, larger cluster, or to show several images, with different sets of relations of the instance or concept.

The best graphs are those that are composed by hand, but drawing images in an external tool, and uploading them to the DSS is time consuming, especially when the ontology is subject to change. Therefore, a tool was integrated into the DSS that allows users to easily compose images of concepts and instances by hand. The tool allows a user to create images for any concept or individual. When a new image is created, the concept or individual it is created for is automatically added. By right-clicking on an item in the image, the user can add any related concept or individual to the image as well. The relations between the concepts and individuals are automatically drawn by arrows.

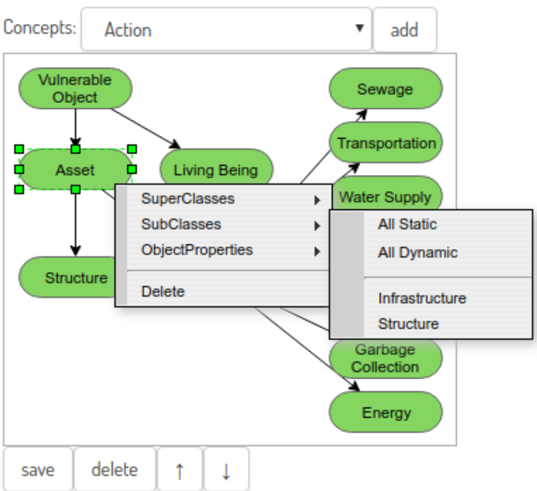

Figure 5: Adding relations to a concept

Every time the image is shown, the entities and relations in the image are checked, and if they do no longer exist, they are also removed from the image. New relations between entities in the image are automatically added to the image. When adding all relations of a certain type, for instance all subclasses of a class, it is possible to set this action to "dynamic" (see Figure 5**Error! Reference source not found.**). When relations are added in dynamic mode, when, at a later date, the ontology is extended and new relations of this type are created in the ontology, they are also added to the diagram. This way the diagrams are always up-to-date, even if the layout might need to be corrected a bit manually.

DATA ANALYSIS AND DECISION SUPPORT

As already described previously, the main operation of the beAWARE ontology is to semantically fuse information from different sources (i.e. analysis results from the various analysis components of the framework) and to subsequently provide a contextualized overview of the crisis situation. The key aim is to support end users with combined information, which will form the basis of and assist them in decision making for crisis response. This represents the *Decision Support* step of our sensor to decision chain.

A dedicated software component called *KB Service* (*KBS*), serving as the interface with the knowledge base/ontology, is also responsible for the semantic fusion of the incoming analysis results. Each analysis component provides its results in JSON format, and KBS's role is to parse these results, and to generate and add respective instances to the ontology. Independently from their source, all results will lead to creating instances of media items, tasks, datasets, incidents and vulnerable objects (see subsection "Representing Analyzed Data").

A set of *SPARQL*[3] rules (W3C, 2012) running "on top" of the ontology are responsible for performing further inferences. Representative examples include the following:

- Grouping incidents taking place in neighboring locations together under a common "umbrella" incident;
- Calculating incident priority levels, e.g. an incident where people are in danger has higher priority than an incident where traffic is reported;
- Calculating incident certainty, severity and potential impact.

For example, a sample query that retrieves all the incidents classified as "highly likely" (i.e. have a confidence score of at least 75%) is illustrated in Figure 6.

```
SELECT DISTINCT ?incident
WHERE {
    ?incident rdf:type :Incident .
    ?detection rdf:type :Detection .
    ?detection :detectedIncident ?incident .
    ?detection :hasConfidenceScore ?score .
    FILTER(?score >= 0.75)
}
```

Figure 6: SPARQL query that retrieves all highly likely incidents.

The results of the above inferences are appended to the ontology. With the initially asserted and the subsequently appended inferred knowledge, the ontology may enter the decision support mode, during which it is able to respond to a wide variety of queries; in knowledge engineering, these are typically referred to as *Competency Questions* (*CQs*). The list of CQs was jointly created by the knowledge engineers of beAWARE and end-users and includes queries such as:

- Which location is the one with the most/least incidents?
- Which and how many vulnerable objects (e.g. persons, buildings, and assets) are at risk at a specific location?
- Are people at (or approaching) a location at risk? (e.g. a flooded location)
- Which location is the one with the most people (or buildings, or any other specific type of asset) at risk?

Each CQ is again formulated as a SPARQL query; CQs may either be submitted to the ontology at periodic intervals (e.g. every 1 minute), or, alternatively, the end-user may explicitly request that the CQs be submitted at a specific point in time. Depending on the result set, the user interface has to be updated accordingly (e.g. a change in the colors of pins on the map, or alerts displayed to the operators in case people are in danger). Such a sample query that retrieves the location with the most incidents is displayed in Figure 7.

[3] SPARQL is a set of specifications for querying and manipulating ontology models.

```
SELECT ?location (COUNT(?incident) AS ?countOfIncidents)
WHERE {
    ?incident rdf:type :Incident .
    ?location rdf:type :Location .
    ?incident :hasIncidentLocation ?location .
}
GROUP BY ?location
ORDER BY DESC(?countOfIncidents)
LIMIT 1
```

Figure 7: SPARQL query that retrieves the location with the most incidents.

Nevertheless, this is an ongoing work with still a few notions left that should be added to the ontology, in order to better facilitate the whole decision support process. The key notions that are currently missing and are planned to be integrated in the next revision of the ontology are the responder units and assigned actions, as well as a variety of stakeholders and their respective roles.

CONCLUSIONS AND FUTURE WORK

This paper presented the sensor to decision chain, which gets currently applied to three large scale use-case tests. The goal was to use and test existing standards and tools like the Sensor Things API and combine it into a methodology which can be applied to DSSs. The applied SensorThings API proved to be very helpful to solve the problem of harmonizing heterogeneous data and making it easily accessible from different processing services. Additionally, the developed beAWARE ontology had to integrate the knowledge of multiple domains and therefore, required the interaction of multiple domain experts. Using an online tool which supports a graphical visualization speeds up the process. The ontology can be used as a basis for many more research projects which will tackle the problems of climate change and involve a set of heterogeneous sensors and processing algorithms.

Regarding future work, besides the various additions to the ontology model discussed above, further research will focus on the reasoning techniques which will be applied to the semantic data. One example for that is generating automated warnings (including reports) based on the current situation and respective context stored in the knowledge base. Another imminent step is to have end-users evaluate the ontology-based decision support and the recommendations provided by it. This assessment will take place in a few months' time, when the first pilot deployments will be evaluated in the field, and our findings will then be publicly released.

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