The backbone of decision support systems: the sensor to decision chain

Philipp Hertweck[1]
Jürgen Moßgraber[1]
Efstratios Kontopoulos[2]
Panagiotis Mitzias[2]
Tobias Hellmund[1]
Anastasios Karakostas[2]
Désirée Hilbring[1]
Hylke van der Schaaf[1]
Stefanos Vrochidis[2]
Jan-Wilhem Blume[1]
Ioannis Kompatsiaris[2]

[1] *Fraunhofer Institute of Optronics, System Technologies and Image Exploitation IOSB, Germany*

[2] *Information Technologies Institute, Centre for Research and Technology Hellas, Greece*

ABSTRACT

Understanding the current situation is critical in every natural disaster or crisis. Therefore, there is a need for accurate and up-to-date information about the scope, extent and impact of a disaster. The basis for this information is data that is available through a variety of sensors. Decision Support Systems (DSSs) support decision makers in disaster management, response and recovery by providing early warnings, insights into the current situation and recommendations for mitigation actions. For this purpose, raw sensor data needs to be collected, analyzed, integrated, and its semantics need to be automatically understood by the system. This series of processes forms a generic sensor to decision chain. In this paper, we present solutions and technologies to integrate those steps seamlessly, also demonstrating how each step of the pipeline can be visualized.

Keywords: Sensors, Internet of Things, Data Integration, Data Aggregation, Semantic Modelling, Ontologies, Reasoning, Decision Support, Early Warning, Crisis Management, Visualization

INTRODUCTION

The World Meteorological Organization expects a global temperature increase of 3°C caused by climate change (World Meteorological Organization, 2018). This increases the probability for the occurrence of critical natural events, such as floods, dry periods (resulting in forest fires) or heatwaves. To face these challenges, the United Nations have called to intensify the development of early warning systems (UNISDR, 2005). In 2015, the call was renewed, now also including chained disasters (UNISDR, 2015). Through the support of early warning and risk management systems, authorities aim to limit the impact of natural disaster crises.

In this paper, we propose a generic approach to improve the quality of decision support and foster early warning systems. Our method, called the "*sensor to decision chain*", covers the steps from sensor data acquisition[1], semantic data analysis, data integration and eventual decision support. The chain forms the basis of an integration framework supported by a variety of cutting-edge technologies. Therefore, the main goal of the framework is to support authorities through a decision support system that implements the sensor to decision chain.

The following subsections describe each step of the sensor to decision chain and present appropriate technologies for its implementation. The rest of this paper is structured as follows: Section "Background" discusses existing decision support workflows and respective implementations; "Motivation" presents the beAWARE project, which serves as a practical example of our implementation and offers the possibility to test our approach in three large-scale pilots; the general approach is discussed in "The sensor to decision chain" section, followed by an thorough description of each step. Finally, "Conclusion" summarizes our findings and discusses directions for further research.

BACKGROUND

Since the 1980s, computer systems provide decision support to human actors in complex situations. A decision support system (DSS) is an interactive computer-based system, which supports decision makers in solving unstructured problems by using data and models (Sprague, 1980). In their recent survey on current decision support systems for natural hazard risk reduction, Newman et al. (2017) assessed the capabilities and drawbacks of DSSs with the help of a classification system and found that a key shortcoming of current approaches is the limitation to single hazard situations. Based on our "*sensor to decision chain*", we propose to overcome this limitation through a flexible framework of sensors and semantic components, allowing the integration of various data sources. This exactly is the main contribution of this work in comparison to other related works in the literature. We present below a subset of representative examples from existing approaches.

Fang et al. (2014) propose a DSS for environmental monitoring that integrates various technologies, like Internet of Things (IoT), Cloud Computing and Geographic Information Systems (GIS). The authors pointed out the importance of data acquisition and data fusion and proposed a layered architecture, which we also adopted to some degree in our sensor to decision chain. Similarly, di Pietro et al. (2017) discuss a DSS for crisis management based on an architecture structured along functional blocks, covering different aspects in crisis management like monitoring natural phenomena or predicting damage scenarios.

However, neither of the aforementioned approaches considers adding a semantic integration layer for integrating the various data sources. Nevertheless, semantic technologies play a vital role in modern DSSs and their deployment has indeed been discussed in recent works. Indicatively, Wanner et al. (2014) present an ontology-structured knowledge base, which helps deduce information relevant to the specific user that is communicated in the language of their preference. Moßgraber et al. (2015) demonstrate another usage of semantic technologies, where an ontology is used to improve the understanding of the use case domain, as well as to structure and visualize information of the current situation. Finally, Burel et al. (2017) encapsulated a layer of semantics into a deep learning model for automatically classifying information from social media posts.

The deployment of semantics is also adopted in early warning systems, which constitute a specific type of DSS. Moßgraber (2017) provided an overview of current architectural designs and technologies for such

[1] In the context of this paper, a sensor is a device that delivers data about an ongoing crisis. This explicitly contains sensors delivering unstructured information, such as pictures, recordings, videos or even data from social media.

systems. The operation of such DSSs is complex and challenging. Therefore, in order to facilitate the development of new DSSs, Moßgraber developed, based on the aforementioned overview, a framework for the architecture of next generation early warning systems. This framework includes semantic technologies and workflow automation. Moreover, Poslad et al. (2015) presented an Internet of Things (IoT) early warning system for environmental crisis management, where the deployment of semantics facilitated sensor and data source plug-and-play, offering simpler, richer, and more dynamic metadata-driven data analysis and easier service interoperability and orchestration.

Finally, research and development has been invested in crowdsourcing as well. For instance, the Finnish Meteorological Institute (FMI) offers a way to report weather measurements through a mobile application. Furthermore, the *Ushahidi* platform was developed as a response to riots in Kenya after the 2007 elections, in order to report and document such incidents (Okolloh, 2009). Since then, the system has been extended to be applicable to other events as well. A student project from the University of Bremen developed a mobile application that collects reports during a crisis and offers means of communication with the involved people (Frommberger, 2013). Finally, the *i-REACT* project (http://www.i-react.eu/) is going one-step further by integrating messages from citizens as well as first responders into a decision support system. The focus of all those projects is the collection of reports from citizens. Yet, integration into a bigger system, offering sophisticated analysis capabilities, is not foreseen.

MOTIVATION

This section outlines the need for an integrated platform for data acquisition, analysis, evaluation, and visualization for DSSs with the help of project beAWARE (Enhancing decision support and management services in extreme weather climate events – http://beaware-project.eu/). The main goal of the beAWARE project is to provide an integrated decision support solution, covering all phases of an extreme weather event. Next to *situational awareness*, *command and control* aspects were considered as well. To provide sophisticated *situational awareness* capabilities, all phases need to be considered, from forecasting and early warning before the crisis, as well as informing authorities together with workforce management while the event is taking place.

During the pre-warning phase, when a critical situation is predicted before it comes in effect, the extent of the disaster should be estimated through forecasts and with the help of available knowledge. This information can be used to dispatch early warnings, allocate first responder forces and prepare for the event, in order to reduce its impact as much as possible. Once the disaster occurs, it is important to get accurate information about scope, geographical distribution, affected people and assets as quickly as possible. In a natural disaster event, it is important to know what happened in previous (comparable) events, what is happening in this moment and what can happen in the context of the event. *Situational awareness* requires the collection of available information in (near) real-time, as well as background knowledge and experiences of past events. This information supports the *command and control* of the available workforce and other resources to mitigate the effect of the critical event.

The sensor to decision chain provides a generic approach to facilitate decision support and early warning by drawing a picture of the ongoing situation through available sensors and their raw readings. Key challenges include the collection of data from heterogeneous sources (such as environmental data, social media, first responders and people in danger), data analysis and integration, as well as deducing and extracting important information and presenting it to the responsible persons.

Pilot Use Cases and Sensor Data

To ensure the usability of the development, the work relies on the use cases and the feedback of the end-users in the beAWARE project. This ensures realistic scenarios of extreme weather events (flood, fire and heatwave) and heterogeneous data availability. The sensors collecting these data are included in the first step of the sensor to decision chain. Later in the paper, it is argued that the chosen approach is not limited to these scenarios and sensors, but can easily be extended to other events as well. The following subsections introduce the use cases and end-users.

Flood

The flood use case is located in Vicenza, a city in northern east Italy, crossed by the Bacchiglone River. In this area, the Italian Alto Adriatico Water Authority (AWAA) has deployed nearly 50 weather stations, measuring air humidity, pressure and temperature, precipitation and wind, as well as water-level sensors in the river. These sensors are all connected to the Internet and this allows automatically importing the latest measurements into the system. These observations are extremely valuable since they provide reliable real-time information about the situation. In comparison to other extreme weather events, a flood is easier to predict, as precipitation in the river basin can result in a higher water level in the lower parts of the river. To substantiate this prediction, the Finnish Meteorological Institute (FMI) provides the necessary weather data; especially precipitation forecasts are considered. Additionally, through expert knowledge, a prediction model for the water level in the river has been developed. The exceeding of thresholds in these forecasts is the main indicator for an upcoming event, which results in issuing early warnings.

Fire

Similar to the flood use case, the current and predicted weather data, which is periodically updated, are important indicators for fire hazards. A high temperature combined with a low humidity and little precipitation increases the risk of fire. These conditions do not necessarily lead to a critical event, but should draw increased attention. In this case, the fire brigade is set on standby. There are several possibilities to detect a fire. The most efficient and reliable way is to constantly record the area of interest by the means of static cameras and analyzing the data (near real-time) by applying video analysis software. Nevertheless, static cameras and sensors in general are typically expensive in acquisition and operation. Therefore, it is usually not possible to monitor the whole area at risk and other data sources need to be considered. The pilot region for the beAWARE use case is a forest area near Valencia in Spain, where, like in most rural areas, unfortunately no static cameras are deployed. To overcome this, the pilot is supported by the usage of drones, which are capable of monitoring a larger area. By flying over the region of interest, pictures and videos are recorded and analyzed to detect critical events, especially starting fires.

Heatwave

In this use case, the weather situation and forecast are factors as well. In contrast to the fire use case, where a low humidity increases the risk of fire, high humidity increases the severity of a heatwave. To mitigate the impact of a heatwave, it is common to offer citizens the possibility to visit public shelters that are cooled down by air conditioning. For the authorities, the condition and status of these places (e.g. available space, problems with sanitary facilities etc.) is of interest. Collecting this data with technical sensors can be very challenging. Therefore, the people themselves can be considered as an additional data source: by analyzing data from social media (e.g. Twitter) or by using a dedicated mobile application from which people can send multimodal reports (text, audio, images, videos) directly to authorities, one can harvest further helpful information. Citizen involvement is not limited to this use case and can help in other scenarios as well.

The above three use cases describe the variety of sensor data and data sources in the project. By overcoming the challenges of heterogeneity, one can offer a detailed description of an ongoing disaster. Furthermore, the importance of each sensor type highly depends on the specific use case.

THE SENSOR TO DECISION CHAIN

As already stated, there is a broad variety of sensors available today. Sensors are accessible via Internet of Things (IoT), Machine-2-Machine (M2M) standards, from social media or from a mobile application (human sensors) (Meissen, 2014). To make use of the available data, it needs to be collected and analyzed. This is a prerequisite for gaining a better understanding of a crisis, for finding critical events like people in need of rescue or for coordinating countermeasures.

To approach this problem Moßgraber et al. (2018) presented a generic approach for decision support and early warning in climate-related crises by applying a pipeline to get from raw sensor data to a model about the ongoing situation (see Figure 1). The key contribution of the paper at hand is to provide tools, models and technologies to execute and visualize this pipeline. The parts of this method cover the steps from sensor data acquisition, data integration and aggregation, semantic modeling and data analysis to provide decision support and early warning capabilities. The challenge of integrating a variety of heterogeneous sensor data to understand the current situation often occurs in the context of crisis management. The presented approach offers the needed flexibility to be applicable for a broad variety of situations. We show this by applying it to three different large-scale use cases within the beAWARE project.

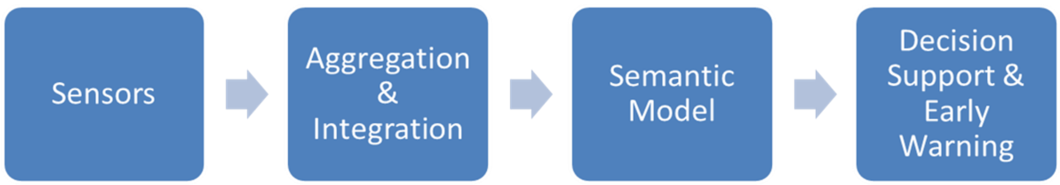

Figure 1: The sensor to decision chain

As a first step, the data needs to be collected from the sensors. It then needs to be aggregated, fused and analyzed to understand the semantics. A *knowledge base* (*KB*), formalized as an *ontology*, provides a global schema to support the semantic integration from heterogeneous sources (Noy, 2004). The ontology describes the concepts of interest and their interrelationships, covering various domains like sensor metadata, climate change and crisis management. Once the schema is established, it can be populated with results from various analysis components processing the raw sensor data. Since the KB knows not only the plain data but also its underlying semantics, a DSS can recommend actions or provide information about the situation.

In the following sections, each individual step is presented in detail. After a generic description, applicable techniques and technologies are presented. Then we will show how the aforementioned use cases can be implemented with our approach, including visualizations adjusted to specific stakeholders, who interact with the sensor to decision chain.

SENSORS

To allow well-grounded decision support and early warning, reliable up-to-date information is crucial. Usually it is not possible for decision makers to visit the affected area of the crisis in-situ, and it is not possible to overview all relevant aspects without technical support. Therefore, the situation needs to be captured by sensors, to be considered in the decision making process. In the use case section, necessary information and their possible sources have been presented. This section will present three generic types of sensors, their characteristics and the existing challenges. These categories are namely static sensors in the context of IoT, social media, and mobile app technology. Depending on the use case, available resources and infrastructure, the appropriate sensors to be used need to be selected.

Static Sensors and IoT

Spatially distributed static sensors can observe a specific area. There are various types of sensors like weather stations, river level sensors as well as video cameras, offering reliable information about the physical phenomena in the covered region. However, they are expensive in installation and operation. Additionally, they usually have a fixed position, which limits the coverage to the deployed area. Still, the upcoming Internet of Things (IoT) technologies lead to a growing market of new and cheap sensors. These devices can be used to deploy additional sensors in the observed area. Despite their lower measurement accuracy when compared to traditional sensors, the correlations of their outputs can lead to valuable insights.

Social Media

Another important data source in a crisis is the public itself. Social media services like Twitter offer new possibilities to retrieve information (e.g. (Terpstra et al., 2012)). A lot of research has been focused on collecting and analyzing social media messages. While collecting this data is comparatively easy, the automated analysis can be very challenging. The content of the message needs to be understood by applying text analysis. Due to the ambiguity of natural language, this process is rather complex. Even more challenging is the individual textual style applied in social media, e.g. the use of abbreviations, hashtags or emojis, which prevents the application of traditional text analysis and content extraction mechanisms.

Besides textual analysis of individual messages, research has been also conducted on clustering and classifying similar messages determining ongoing events (Angaramo & Rossi, 2018). Furthermore, researchers try to derive the sentiment of the message (Schulz et al., 2013) to infer the emotional state of the author.

To utilize this information, the authors and their electronic devices can be seen as a sensor in the sensor to decision chain. It allows insights into incidents, thoughts and feelings that are not directly communicated to the authorities, but are openly available and can be very helpful to get a better picture of the ongoing situation. Still, social media data often has no geo information attached. Thus, if the position of a message is missing (which is the common case) it can only be inferred by applying text analysis. These methods are not reliable through well-known challenges in natural language processing techniques. Additionally, an exact geographic location needs to be mentioned in the text (e.g. the name of a well-known building), which makes assigning social media data to a concrete position rather challenging.

Mobile App Technology

Another communication possibility for the public is a mobile application for user-optimized provision of information. This is a more direct way in comparison to social media: on social media, the recipients of the messages are not clear and people might not be aware that their published information is useful for decision-making. Thus, we are currently working on incorporating data from a dedicated mobile application into the sensor to decision chain (see Figure 2).

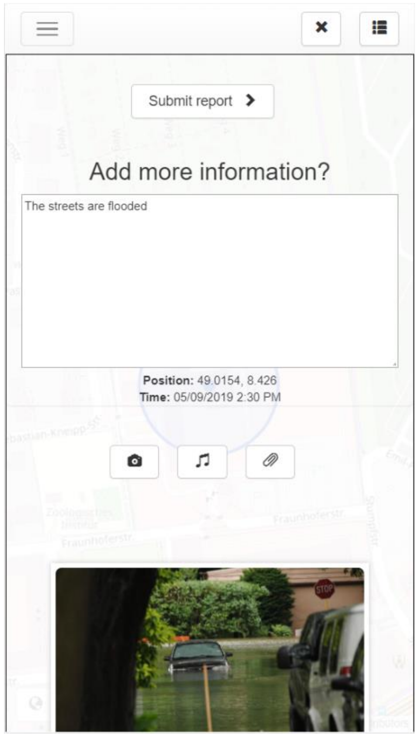

Figure 2: Sending reports from a mobile application

The variety of sensors embedded in modern smartphones can provide precise information. People can choose the appropriate input modality depending on the current situation and their personal preferences. This can be done by allowing text input as well as utilizing the smartphone camera to take pictures/videos or the microphone to record audio. The real world context can be added by utilizing the GPS data of the mobile device.

AGGREGATION & INTEGRATION

The outcome of the first step of the sensor to decision pipeline is raw data. Integrating this data is difficult, because of the multiple ways accessing this data and the different formats in which the measurements and metadata are available. To allow decision support and early warning, the data needs to be harmonized and aggregated in the next step. Just as the sensor selection is dependent on the use cases, the integration step is dependent on the selected sensors. This section will present methods to integrate different types of sensors.

Integrating Time Series Data

The most prominent method to integrate data from various sources is to rely on standards. One example is the OGC SensorThings API (Liang et al., 2016), which offers the possibility to manage time series based sensor data as well as sensor metadata. Besides an underlying data model, an API has been specified, based on the representation state transfer (REST) paradigm, which is very common in the context of web applications (Fielding & Richard, 2002). The REST interface allows easy access from different applications and programming languages. The SensorThings API integrates selection and filter operators from the OASIS Open Data Protocol (Pizzo et al., 2014), which offers the possibility to query data.

Next to this REST-based API, which allows CRUD (create, read, update, delete) operations, a Message Queue Telemetry Transport (MQTT) extension was specified. This allows the notification of new and changed entities through a listener/subscriber pattern. Due to these characteristics, the SensorThings API standard offers an appropriate solution to integrate time series data (like sensor measurements) into a decision support system. In the presented use case scenarios, we use the Fraunhofer IOSB open source implementation of the OGC SensorThings API to integrate measurements from weather stations, river gauges or weather models. To this moment, both current measurements as well as forecasts are stored on the FROST server (van der Schaaf, 2016).

To get an understanding of the current situation and the provided results in the decision support step, transparency of each chain link is crucial. To do so, the data provided by the sensors can be visualized in an interactive graph. Even though this data can be analyzed automatically, it is important to offer a possibility to get a detailed view of single measurements. Experts might have to validate recommendations of the decision support module. In addition, correlations between two measured values can be discovered through visual inspection. Figure 3 shows an example for the correlation between precipitation and water level.

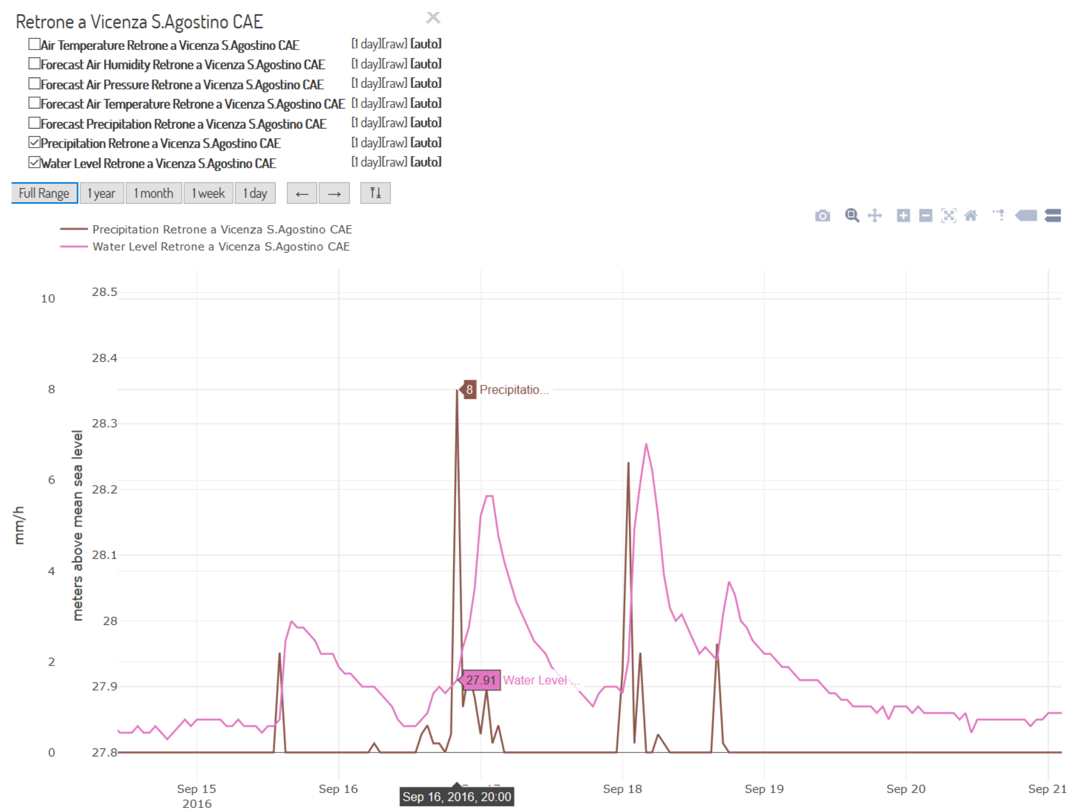

Figure 3: Visualization of precipitation and water level

At this point, we need to keep in mind that the data volume might exceed the volume that can be handled by subsequent modules. A data aggregation step reduces the data amount for further processing and displaying. Examples for aggregation functions are the calculation of average, minimum or maximum values. Another possibility is to monitor the measurements and pass single events to the following steps e.g. the exceeding of a threshold.

Integrating Mobile App Technology

In the background section, we pointed out that there are various mobile applications allowing citizens to provide data to authorities in a crowd-sourcing manner and we pointed out that all of these approaches lack a deep integration into a DSS. To facilitate this, we propose to regard data coming from mobile applications as additional sensor data running through our sensor to decision chain. By this approach, we achieve a deep integration through applying analysis components to this data. Semantically integrating these results allows an automated utilization for decision support as well. The semantic model section demonstrates how this aspect can be integrated in the overall model.

Integration of Analysis Components

Due to the variety and amount of available sensor data, a tight integration is only possible by applying advanced analysis methods. Especially visual content (images, videos) provided by static cameras, citizens or via social media is only helpful when useful information can be extracted in a machine interpretable format. This can be achieved through image and video analysis tools. Audio content firstly needs to be transcribed to written text in order to extract information by applying text analysis and Natural Language Processing (NLP) methodologies.

Certain analysis processes tend to be demanding in processing power and time, vastly depending on the incoming media characteristics (e.g. length, resolution of pictures or videos) and the system's hardware setup. As a result, a large volume of incoming resources can prevent a real-time approach. Thus, from a system architecture point of view, the various analysis components operate independently and provide results asynchronously. For instance, a citizen's submission of data via the Mobile App might contain textual and visual attachments. This results in the creation of an incident report in the main pipeline, which later on will be enriched with findings from the text and image analysis components. Therefore, all analysis components need to monitor all reported data and decide about which data artefact they can provide information.

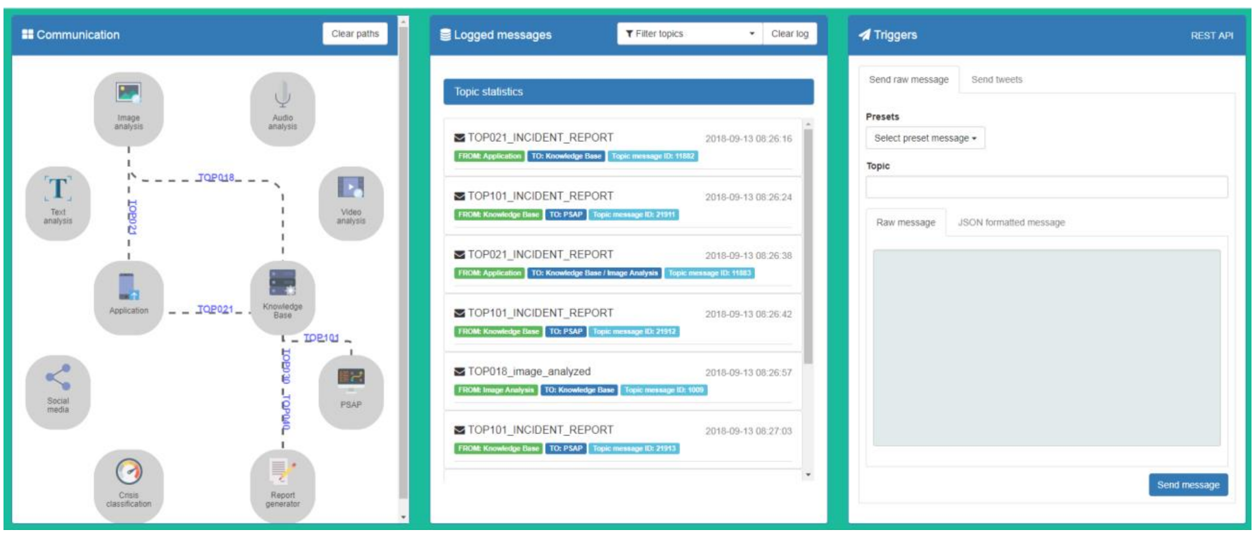

Figure 4: The beAWARE Bus Logger interface

For the implementation of the beAWARE platform, a standalone web application called *beAWARE Bus Logger* (see Figure 4) has been developed to track, log and visualize these asynchronous communications between sensors, analysis components, the semantic model (see next section) and other system modules. This greatly facilitates the establishment and debugging of communication protocols, allowing visual interpretation of the system and providing advanced testing capabilities. However, the Logger is an excellent tool for decision makers to visualize the progress of information exchange during an ongoing crisis.

SEMANTIC MODEL

This section describes the *semantic model* of our pipeline, which is formalized as an *ontology* (Gruber, 1993), offering a unified representation of all relevant domain-specific information in a formal way. The ontology is a lightweight model for crisis management in the context of climate-related natural disasters and plays a two-fold role. First, it serves as common uniform model for semantically integrating heterogeneous information from the diverse sources and sensors. Ontologies are an excellent fit for addressing this issue of semantic heterogeneity, and for establishing interoperability through a process called "semantic integration" or, less frequently, "semantic fusion" (Wache et al., 2001). The second role played by the semantic model is serving as the backbone of the decision support system deployed within the context of the beAWARE project (see later subsection).

Contrary to other existing ontologies for crisis management that only focus on specific aspects of the occurring natural disasters, the beAWARE ontology is an all-around model integrating all pertinent aspects, including associated conditions and climate parameters, results of the analyzed data (e.g. text, audio, images, videos), as well as workforce management. Nevertheless, parts of the ontology are inspired from existing models for representing similar notions. *MOAC (Management of a Crisis)* (Ortmann et al., 2011) constituted the basis of our representation for disaster impacts, *SoKNOS (Service-Oriented Architectures Supporting Networks of Public Security)* (Babitski et al., 2011) was adopted to categorize damages and resources, and the *PESCaDO* ontologies (Rospocher & Serafini, 2012) were extended to represent environmental and meteorological conditions.

The key notions of the beAWARE ontology are presented in (Kontopoulos et al., 2018), while the ontology itself is publicly available (beAWARE, 2018a). Figure 5 displays an overview of the main concepts and their relationships, based on the Grafoo notation for ontology visualization (Falco et al., 2014).

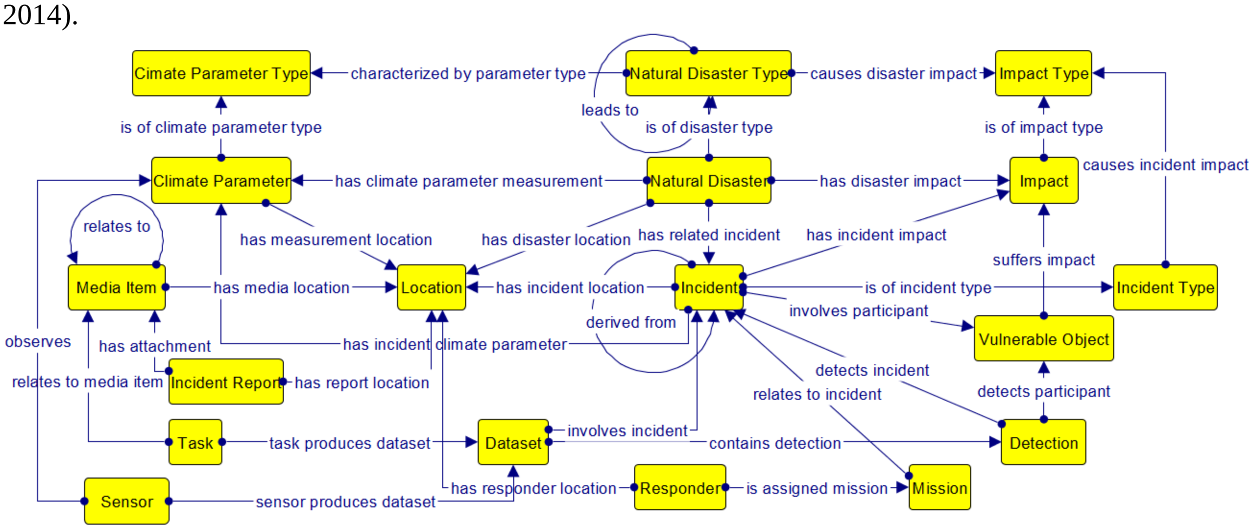

Figure 5: Main concepts of the beAWARE ontology

In order to assist the unfamiliarized users and to encourage further ontology reuse, the beAWARE model embodies extensive definitions and representative examples, via the use of SKOS properties `skos:definition` and `skos:example`, respectively (Miles & Bechhofer, 2009).
The following subsections briefly present the various representational aspects of the ontology.

Natural Disasters

To understand the crisis and to provide decision support, a basic understanding of the underlying phenomena is needed. The involved concepts are visualized in Figure 6. In our presented case of climate-related crises, a *Natural Disaster* is the main concept. Figure 7 shows a possible instantiation for the UK heatwave that occurred in between the 17th and 22nd of June, 2017 (BBC, 2017). This particular disaster is characterized by a *Natural Disaster Type*, in this case "*heatwave*". By using this modelling approach, other types of natural disasters like floods, forest fires, storms or earthquakes can be categorized as well.

Disasters can interfere among one another (modeled by the *leads to* relation): e.g., a heatwave may lead to forest fires or a storm may lead to floods. Each *Natural Disaster Type* is characterized by measurable parameters, the types of which are modeled as *Climate Parameter Types*. Their concrete manifestations are instances of a *Climate Parameter*, which are described by a measured value in a specific unit at a specific time. Since those measurements are conducted at a specific location, the *Climate Parameter* concept has a relation to the *Location* concept. Furthermore, to describe the effects of natural disasters, the *Impact* concept is introduced (analogous split into *Impact Type* and *Impact*). To limit the extent of an impact, counteractions might be needed; we refer to such problems that can be tackled by an action as *Incident*. In the next sections, we can see that the *Incident* is relevant in all the three domains of our ontology.

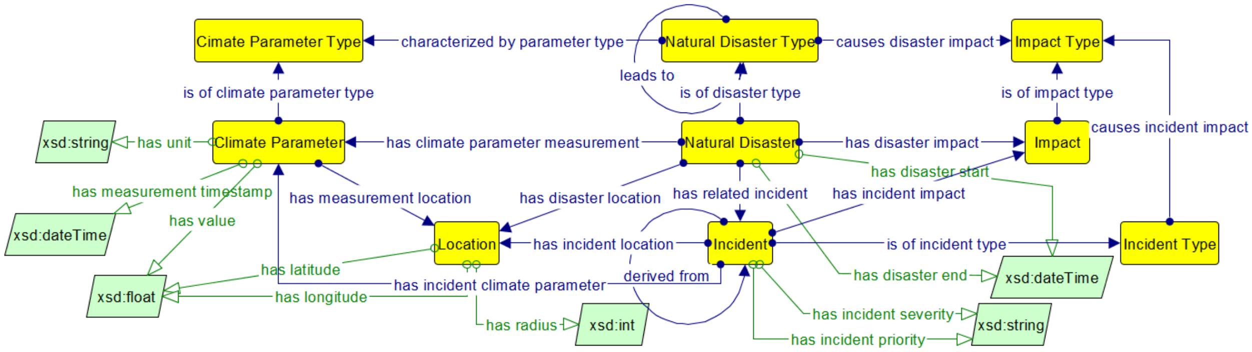

Figure 6: Model of natural disasters together with impacts and risks

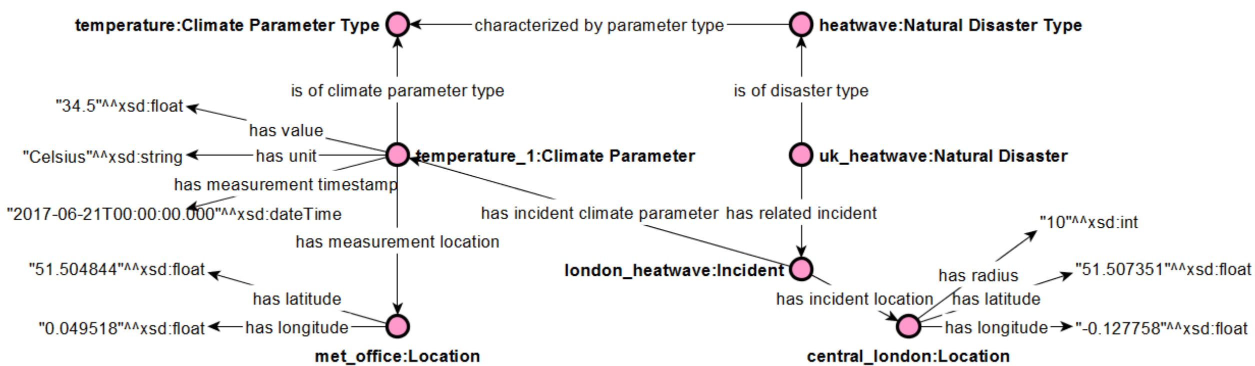

Figure 7: Instantiation of a concrete natural disaster

Sensors and Analysis

Information about the ongoing situation is fed into the system by sensors and it is automatically analyzed by the appropriate analysis components. These results are semantically integrated into the beAWARE ontology, as shown in Figure 8. The raw data is represented via *Media Item*. An instance of a *Task* analyzes a *Media Item* and produces a *Dataset*. Analyzing tasks might be the processing of a video or image analysis component, where the *Dataset* contains the relevant output, which is mainly a set of *Detections*. Each *Detection* is described by a confidence degree, denoting the probability of the detected element by the analysis component. Objects involved in an *Incident* are *Vulnerable Object*s (e.g. assets, persons, infrastructure, buildings, etc.). They can be distinguished by extending the *Vulnerable Objects* concept by corresponding sub-concepts, which are not displayed. Additional properties, like *detection risk* or *severity level* can be added to the detection. The relation of a media item to an incident can be given directly or it can contain a location, from where the incident can be inferred. The relations from *Datasets* and *Detection* to *Incident* can be inferred from the *Media Item*, and can be inserted manually or can be asserted as a result from the analysis.

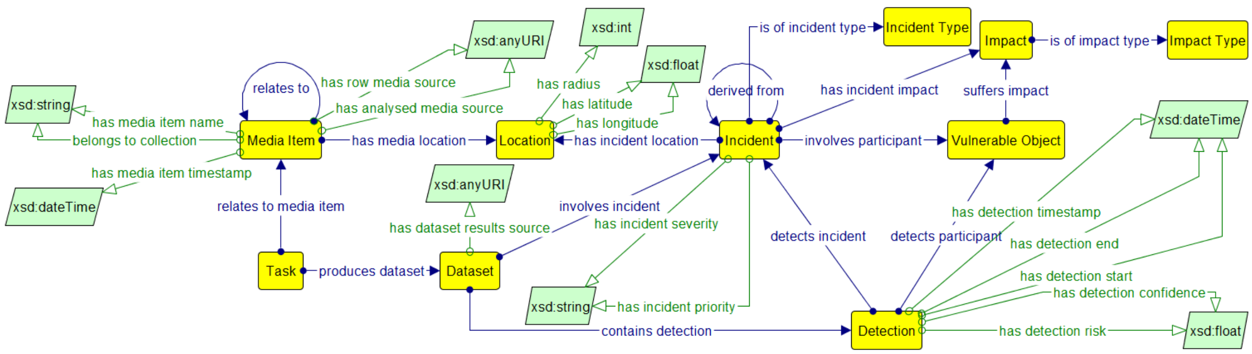

Figure 8: Representing sensors and analysis

First Responder Units and Assignments

Managing a crisis is only possible through the coordinated use of available forces. Therefore, first responder assignments are also part of our semantic model, as shown in Figure 9. A first *Responder* might be assigned to a *Mission*, which is characterized by several properties like *status* or *priority*. A mission is related to an *Incident* and therefore mitigates an *Impact*. To get an overview of locations of the available forces, the current location of a first responder is modelled as well.

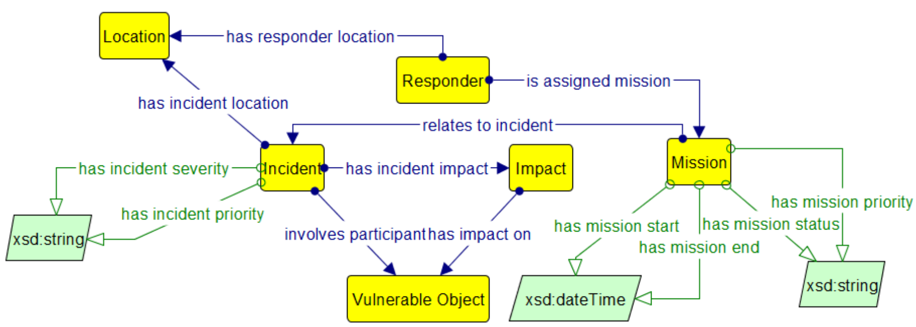

Figure 9: Rescue teams and assignments

Visualization of the Ontology

An ontology covering several domains and topics can be extremely complex and sophisticated. Therefore, visualization plays an important role in (a) helping end users to understand the model's inherent structure, enabling them to work efficiently with the ontology, and, (b) giving a more thorough overview of an ongoing crisis and its potential impacts, thus, improving the quality of decision support. Besides the visualization of the structure, the contained data (e.g. specific instances, measurements and incidents) needs to be displayed as well. Therefore, our implementation of the sensor to decision chain also contains a module to visualize the ontology (structure and instances), offering an additional tool that supports decision makers by providing a clearer picture of the underlying model, data and situation. In this context, we implemented an interactive visualization that allows browsing and analyzing the complete semantic content.

The fully automated generation of graphs of an ontology is difficult, since the importance of individual parts is highly dependent on the use case. While displaying all concepts and their relations might lead to an unmanageable amount of information, we decided not to adopt an automated generation approach. A full manual solution, on the other hand, would involve the use of an external tool to generate a visualization and uploading the result. This is very time-consuming and error-prone, especially when the underlying ontology is changing. Hence, we are implementing an integrated solution. By following this approach, there is the guarantee that the visualization matches the currently used ontology and therefore avoids inconsistencies, which may prove too confusing for users. Thus, a tool was integrated into the DSS to allow end users to compose images of the ontology, including both concepts as well as instances. When creating an image, the current concept or instance is automatically added. Related concepts and images can be added for each item in the picture, by selecting them from the recommended list, which is automatically populated with all related elements existing in the underlying ontology. This allows the automatic naming of the relations (drawn by arrows) and ensures that the picture is aligned with the ontology. This accordance is verified every time the image is shown. Entities that no longer exist are removed automatically. Applying relations dynamically to the image (see Figure 10) ensures that relations added to the ontology at a later point in time are automatically added to the image, without further interaction of the user. Depending on the use case, different relationships are of interest each time. It is possible to attach multiple ontology images to a concept or instance. This allows the visualization of different aspects.

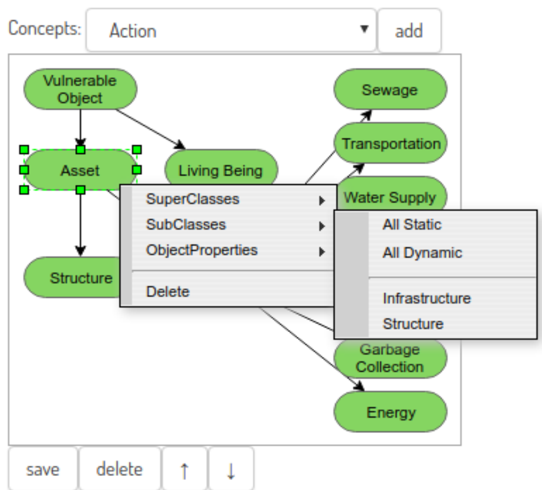

Figure 10: Creating a visualization of the ontology

Figure 11 shows the visualization of an instance. The instance itself is described through text and image. On the right side, the concept of that instance together with all relations is shown. At the bottom, there is the ontology visualization, showing the relationship of that instance with other concepts. Since these concepts and relationships on the right-hand side are linked to the target entity, the ontology can be easily browsed and analyzed.

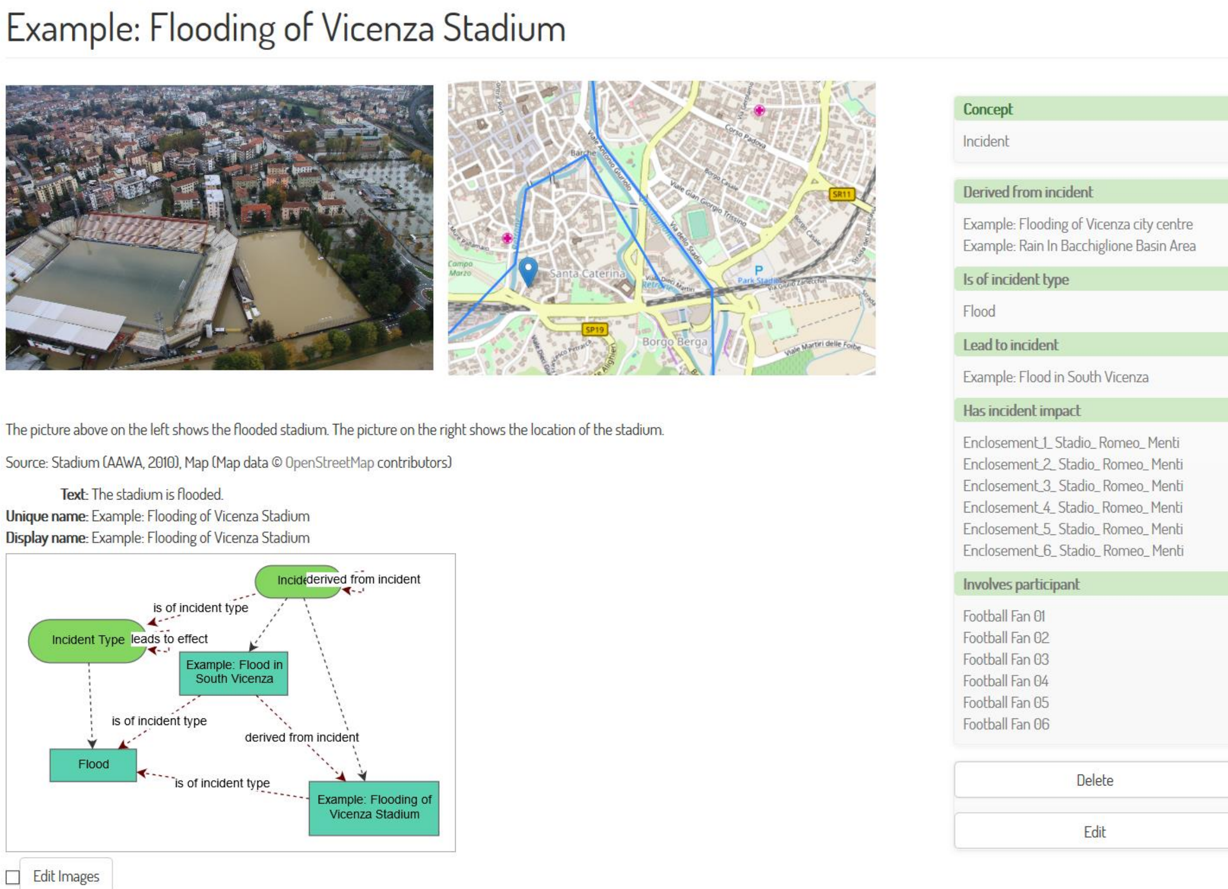

Figure 11: Visualization of an instance

DECISION SUPPORT & EARLY WARNING

The last part of the sensor to decision chain is decision support and early warning. All previous modules work towards this step by collecting, analyzing, integrating and modeling the input data. Decision support and early warning aims for the generation of an accurate model of the current crisis that contains past information (experiences of previous events), current real-time information as well as predictions and forecasts. The main goal is to capitalize on this model for supporting end users in decision making for crisis response.

One aspect of decision support and early warning is the monitoring of available data to detect critical situations in an early stage. This can be achieved by continuously evaluating predefined metrics, which can directly be derived from sensor values (e.g. current water level) or from more complex relations (e.g. used capacity of rescue forces). In addition, they can refer to a single point (e.g. current water level at specific latitude/longitude coordinates) or a region (e.g. rescue forces in this area). Next to metrics, which can be grouped geographically, the data model can be observed regarding critical events that require an instant action by a rescue team (e.g. a static camera captures an incident with injured persons).

Decision support and early warning are very use-case specific. Therefore, in this subsection we demonstrate only a proposed generic approach based on a flexible query mechanism for providing authorities and human operators with decision support and early warning capabilities. The concrete implementation each time needs to be materialized when applying the sensor to decision chain methodology to specific use cases.

Therefore, starting with the risk assessment phase (i.e. before a disaster actually occurs), the Crisis Classification (CRCL) system, which is the main component responsible for this task fuses and analyses information acquired from heterogeneous data sources, in order to support authorities and local stakeholders during the risk assessment as well as during the decision making process. To achieve this, the system has been equipped with functionalities and capabilities to collect multiple types of data and information related with the crisis during the emergency phase. Specifically, sensing data from weather stations, as well as aggregated data from other components, are available to CRCL for assessing the risk and for classifying the impending crisis. Thus, a proposed holistic multimodal fusion approach considers the analysis results from multimedia analysis, including image, video and audio analysis, multilingual text analysis, mobile applications for citizens and first responders as well as social media.

Entering the phase when the disaster is ongoing, in order to retrieve information from the semantic model, integrating all the relevant knowledge, SPARQL can be used to query the information and derive inferences. SPARQL is a set of specifications for querying and manipulating ontology models, standardized by the W3C (W3C, 2012). The expressive power of SPARQL allows not only the retrieval of explicitly asserted data, but also inferring new information via calculations or semantic reasoning. For example, incidents can be spatially grouped, so that events happening very close to each other are visible as a single event. Another example is the automated rating of events based on their severity (see Figure 12). This can be done by utilizing the analysis results, especially when people are involved.

```
SELECT ?disaster ?incident ?severity
WHERE {
    ?disaster rdf:type :NaturalDisaster .
    ?incident rdf:type :Incident .
    ?disaster :hasRelatedIncident ?incident .
    FILTER (?severity = "high"^^xsd:string)
}
```

Figure 12: SPARQL query that retrieves all high severity incidents

In addition, it is possible to dynamically calculate an incident's certainty, severity and potential impact, based on the available information. For instance, Figure 13 displays a query for retrieving fire or flood incidents involving at least one human, which can then be assigned with a high priority.

```
SELECT DISTINCT ?incident
WHERE {
    ?incident rdf:type :Incident .
    {?incident :isOfIncidentType :Fire .} UNION {?incident :isOfIncidentType :Flood .} .
    ?participant :participantIsInvolvedIn ?incident .
    ?participant rdf:type :Human .
}
```

Figure 13: SPARQL query that retrieves incidents involving at least one human

The inference results can optionally be appended to the ontology in order to retrieve them in further queries. In knowledge engineering, queries which can be answered by the use of an ontology are typically called *Competency Questions* (*CQs*). In the context of our use case, a list of CQs was created, which assisted in formulating a list of initial requirements for the decision making process. Each CQ was formalized as a SPARQL query to be answered by the semantic model. The full list of CQs, together with the corresponding queries, can be found online (beAWARE, 2018b) and some indicative sample queries are:

- What are the locations affected by a natural disaster?
- What are the impacts caused by a natural disaster?
- What are the vulnerable objects that suffer the greatest risks?
- Which rescue unit is assigned the most severe incident?

Those CQs need to be executed and evaluated and the execution of the respective SPARQL queries must be explicitly triggered. This can be done at periodic intervals (e.g. every minute) or on explicit request by the end-user (e.g. because the user is currently analyzing a given situation).

To reduce unnecessary evaluation that would consequently increase the response time, it is also possible to estimate the importance of data that is added to the ontology. Based on this, trigger rules for the CQs can be created. This possibility has not been evaluated yet, but will be part of our future research.

As already mentioned, our sensor to decision chain will be evaluated in three pilot use cases, based on the outcomes of which, decision support and early warning capabilities will be extended in the future. The use of SPARQL query capabilities allow an easy integration of further CQs.

PILOT EXECUTION

At the point when writing this article, two out of three use-case tests have been executed successfully. Each pilot was split into two sections executing the same scenario: one time using legacy tools and one time using the beAWARE platform. In this platform, the sensor to decision chain, described in this article together with the presented technologies was deployed. The double execution of the pilot enabled a direct comparison of crisis management between the currently used tools and the support of the beAWARE platform.

In November 2018, a heat wave was simulated in Thessaloniki, Greece. Due to high temperatures, the authorities decided to warn the citizens and they provided recommended actions, which included visiting air-conditioned places. The main task of the authorities was to monitor the capacity of places of relief (public buildings with air condition), as well as the traffic situation, in order to facilitate the way to those places. The situation on the street as well as in the buildings was reported by citizens either through the mobile application or through Twitter. It has been shown that using the integrated and processed data increased the overview of the authorities to manage the situation in comparison to the legacy tools, like e-mail, phone or radio. A detailed evaluation of the pilot can be found in the publically available deliverable (Lombardo et al., 2018).

The second use-case test took place in Vicenza, Italy. A flooding of the city center was simulated: due to heavy precipitation, the water level of the Bacchiglione River increased. Since the forecasts of the water level prediction model exceeded the normal thresholds, the emergency protocol was activated by the authorities, which triggered precautionary measure in the city. These tasks were arranged, organized and monitored with support of the beAWARE platform. Weather forecasts, water level measurements and predictions together with reports coming from the mobile application and Twitter were integrated and shown to the authorities to help them better understand the situation. A full description of the steps executed during the pilot can be found in the publically available deliverable (Muhic et al., 2019). A detailed evaluation is currently ongoing and can later be found on the beAWARE project website. The pilot execution and debriefing session afterwards showed that the *situational awareness* for the responsible decision maker was higher than when using legacy tools alone.

The successful execution of the two pilots (a third pilot is underway) proved that the methodology described with the sensor to decision chain is fully capable to be applied in crises and it helps to increase the *situational awareness* of the decision maker.

CONCLUSION

This paper presented the sensor to decision chain, which is being applied to three large-scale use-case tests within the beAWARE EU-funded project. A methodology was presented utilizing various sensors and data sources to implement sophisticated decision support and early warning capabilities. Different sensor categories, their integration and analysis capabilities were discussed. A semantic model was shown to allow a common understanding and integration of various data sources. Based on this model, reasoning algorithms are applied to support decision support and early warning. The practicability was proven by the successful execution of two pilot use cases. The preparations of the pilot use cases have shown that all end user requirements can be realized by the presented methodology. It turned out that the semantic model can satisfy its role as the central integration point. On the one hand, it was possible to integrate new use-case specific sensors and, on the other hand, use-case specific decision support capabilities were implemented by formalizing the according SPARQL-queries. Through applying the sensor to decision chain, analysis and integration techniques are available for all integrated data. It turned out that the ontology covered all the needed aspects, with the exception of slight extensions being adopted to fully support all aspects of the use cases. This, however, does not limit the applicability of our approach. The sensor to decision chain describes a methodology along with respective technologies to facilitate decision support and therefore it is not directly visible by the decision maker. In any case, visualizing each step, making the chain transparent and decisions comprehensible is a key challenge to increase the acceptance by all involved users.

In future work, it should be evaluated what kind of additional data can be integrated into the sensor step. It should be examined if static data sources (like topographic information, building development and points of interest) can be used to improve decision support capabilities. A first attempt has already been conducted in including external sematic data sources. In addition, adoptions to the semantic model might be considered to represent the new aspects. Further research needs to be conducted on reasoning techniques applied to the semantic data in addition to the described query mechanisms. This will allow more advanced decision support and early warning capabilities, e.g. generating automated warnings or reports of the current situation. Finally, the practical evaluation of the beAWARE DSS, which is based on the sensor to decision chain methodology, is still ongoing. First results are available and proved the applicability of our approach, while the final results will soon be available.

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