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Reasoning on Semantic Sensor Streams for Smart City

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Abstract

We propose an architecture for knowledge integration and reasoning on real-time heterogeneous data sensors. The system is demonstrated in the public transport scenario. Sensor and urban ontologies are used toghether to fill the gap between low level sensor data and high level optimisation decisions.

Keywords: semantic reasoning, C-SPARQL, smart city.

1 Introduction

Traffic control systems represent one of the main application of the Internet of Things technology in the context of smart cities [3]. With the development of sensor networks and stream reasoning, valuable technological support for accessing rapidly changing data is provided. Yet, there is a lack of systems designed to manage them at the semantic level. The proposed reasoning algorithm aims to determine the number of people who would probably take a public means of transport, based on real-time data from sensor data.

2 System Architecture

The top level architecture highlights three layers: presentation, business and data layer (see figure 1). The interaction is achieved by sending a request from the mobile phone application. The application consists in a map where the current position of the user is indicated. Users

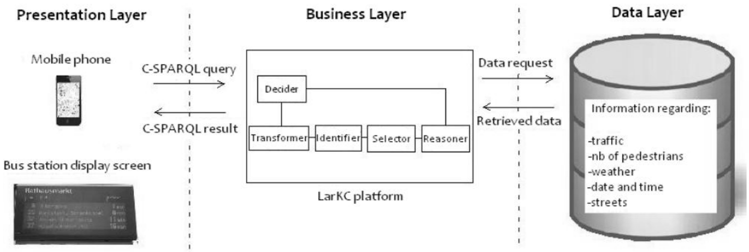

Figure 1. System architecture.

can register their destination and can ask for routes or the time of arrival for a specific bus. For the business layer, we adopted the Large Knowledge Collider (LarKC), a platform for massive distributed reasoning that removes the scalability barriers of currently existing reasoning systems for the Semantic Web. Knowledge about street topology and amenities come from OpenStreetMap in XML format. The pedestrians movement and their destinations are captured and recorded by the wireless network center. The weather and traffic information are gathered from sensors and cameras around the city. These heterogeneos data were integrated to optimise traffic.

Knowledge Representation. Data is collected from various types of sensors: temperature sensors ("Sensor T15 has a temperature reading of 17 C"), from the humidity sensors ("According to sensor H21, precipitation risk is 40 percent"), data regarding time and date ("Tuesday, April 15, 2012, 15:05"), traffic data from cameras and sensors located on route to destination ("Data from cameras C16 and C17 show a 65 percent congestion probability"), information about amenities in a particular area ("According to the information extracted from OpenStreetMap, there is a school in the given area"). We developed the sensor ontology for structuring sensor related knowledge. Figure 2 depicts the temperature and humidity sensor. Concepts are represented by ellipses, roles by arrow, and inviduals by rectangles.

Street topology data was obtained using OpenStreetMap, which

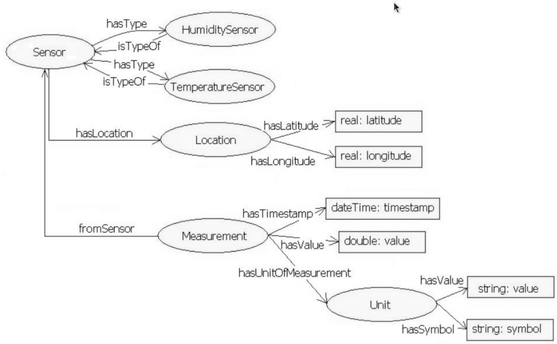

Figure 2. Part of the sensor ontology.

gives users the possibility to choose an area by its coordinates and export it in XML format. The information extracted from the XML files icnludes: knowledge about buildings, knowledge about streets and traffic area, and knowledge about transportation networks. The buildings ontology was used to classify buildings depending on the number of people who attend them. For example, schools and museums will be of type $FrequentlyAttendedAmenity$, given in description logic by $Museum \sqcup HighSchool \sqsubseteq Building \sqcap FreqAttendedAmenity$. Depending on the types of amenities in a given area, the decision of updating or not the public means of transport timetable will be taken.

Reasoning. Streams of data are continuously analysed in order to take decisions in real time. The continuous query in figure 3 counts the number of possible passengers in each station and returns those stations with more than 50 pedestrians.

3 Discussion and Conclusion

The association between data coming from semantic sensor networks and the existing data sources is mandatory in order to achieve high quality process for decision making [2]. Analysing spatio-temporal dy-

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REGISTER QUERY StationsWithManyPassengers
PREFIX s: <http/urbanontology/camera#>
SELECT DISTINCT ?station ?passangers
FROM STREAM <www.camerasensor/cam11.rdf>
     [RANGE 30 MIN STEP 1 MIN]
WHERE {?passengers s:identifiedIn ?station . }
AGGREGATE {(?passengers, COUNT, {?station} )
FILTER (?passengers > 50)}
```

Figure 3. Continuous processing with C-SPARQL.

namics of visitor movements at mass events exploits proximity-based Bluetooth tracking in [4]. In our case, different types of sensors are exploited in order to figure out the situation. In both approaches, one issue regards balancing behavioral privacy and information utility [1].

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