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LINKED DATA APPROACH FOR AUTOMATED FAILURE DETECTION IN SEWER RISING MAINS USING REAL-TIME SENSOR DATA

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The increased availability of sensor data presents opportunities for machine-assisted analytics, reporting and exploration of the sensed environment. Sensor networks provide the ability to observe physical phenomena in real-time and provide useful information to help conservation and management of environmental resources. Thus, exploring these real-time datasets can provide valuable insights for informing policy and decision support in domains such as water quality monitoring, early warning disaster detection, and physical asset degradation monitoring. However, the semantic meaning, format and interface heterogeneity of the sensors and sensor observations are barriers to effective discovery and analysis of events. We propose ontology-driven approaches for performing event detection over real-time sensor data. In this paper, we apply linked data approaches using sensor and domain ontologies for describing sensor observations, event constraints and triggered event notifications for detecting failure in pressure sewers. Specifically, we present a prototype event detection system that implements the above approach for detecting multi-stage fracture failure of PVC and Asbestos Cement pressure sewer mains, that remotely monitor sensor data (i.e. pump flow and wet well levels) and produces event notifications based on sensor observation semantics. The methodology explores how new uses (and additional value) can be found for the large volumes of hydraulic sensor data that organisations such as water utilities already gather in business-as-usual practices.

1. INTRODUCTION

Recent Australian estimates indicate that AU$0.19 Billion a year is attributed to unplanned maintenance activities, responding to failure events in water and sewer networks [7]. Failures in pressure sewers can be particularly severe in terms of direct costs to a water business, but also indirect consequences from social and environmental impacts. There is a clear need for early detection and pre-empting of these failures to minimise response times and reduce consequences [5].

Technologies are now available to provide the means for real-time sensor data to be published and shared with increased connectivity through web services, e.g. GSN [1]. Such technologies can be used for decision support and monitoring of environment and infrastructure assets and provide early warning notifications from data that organizations gather as 'business-as-usual' practice. However, such sensor middleware platforms only provide a partial solution as they can capture information at a level that is too fine grained and difficult to integrate across heterogenous sensor systems [11]. Furthermore, domain knowledge are often localized and known only by domain experts, e.g. pipe asset history and characteristics. Such knowledge is valuable in providing context when responding to pipe failure events, in terms of their impact or risk levels but is not typically captured nor utilized in any formalized semantics, i.e. features of interest, sensors and sensing methods, the observations and its observed properties, quantities and units, and respective water domain semantics.

An approach previously proposed in [9, 10] sought to address the above challenges using an ontology-based approach for complex event processing over a sensor network. In [11], we proposed an *Event Dashboard* for facilitating user-defined semantics for event detection of algal bloom events over real-time sensor data using a set of ontologies to provide a level of abstraction over a range of potentially heterogeneous sensor data sources. This allowed capture of event constraints based on the Semantic Sensor Network (SSN) ontology [2] and our domain extensions.

In this paper, we present an automated failure detection system in pressure sewers using sensor data that is already collected by organizations such as water utilities. The failure detection system builds on the aforementioned previous work. We reuse the ontologies used in the Event Dashboard and extend them to represent the appropriate semantics about pipe features and applicable characteristics for pipe failure detection. We extend the ontology-based approach for complex event processing for pipe failure detection using linked data approaches for posting event notifications such that each notification can be linked to other related sensor, observation, and domain concepts to provide contextual information.

2. DETECTING LEAKS IN SEWER RISING MAINS

Studies in the UK have demonstrated how the long term capture of levels and flows in parts of a gravity sewer network, assist with the identification of anomalies such as blockages and sediment accumulation [8]. A method of detecting such anomalies is to estimate when flow rate from a sewer wet-well into the sewer rising main exceeds a threshold value as this increase in rising main inflow results from the development of leaks in the pipeline which subsequently reduce the level of back pressure resisting pumped flow rates that feed wastewater into the main. As leaks develop in the pipeline, the back-pressure decreases and flow rates increase. However, while leak and burst events are potential causes of observed flow rate increases, it is also possible that secondary events such as occluded air in the pipeline and/or planned maintenance activity on sewage pumps can also lead to flow rate changes that are not directly related to deterioration and failure of rising mains.

2.1. RISK ASSESSMENT OF SEWER RISING MAINS

As a means of providing context to automated event notifications, a simple risk-based scheme was implemented for PVC and Asbestos Cement (AC) sewer rising mains to further support decision making. The intended process is that, in the event of an automated event notification being raised, the scheme is used to determine a risk level associated with a sewer rising main and based on attributes relevant to the likelihood and consequence of sewer main failure. Since deterioration and failure of sewer rising mains depends of pipe material and surrounding environment [3, 4], a multi criteria risk ranking scheme was developed. The criteria and importance weightings for risk assessments in PVC and AC sewer rising mains are shown in the Table 1. The criteria reflect factors that influence the deterioration/failure of PVC and AC sewer rising mains and also the sense in which these factors act, e.g. a PVC rising main installed before 1970 is given a less favourable rating compared to a more recently installed material [3]. The weighting reflects the influence of each criterion over deterioration and failure. The weighted criteria (criterion × weighting) are summed for each sewer rising main and the total score used to assign a risk level (see Figure 1).

Table 1. Criteria for assessing risk in PVC and Asbestos Cement (AC) sewer rising mains

Criteria	PVC	Relative Impt.	AC	Relative Impt.
Pipe installation year	1, 2, 3	2	1, 2, 3	1
Previous burst history	1, 2, 3	1	1, 2, 3	1
Resistance to surge pressures	1, 2, 3	2		
Resistance to cyclic pressures	1, 2, 3	3		
Pipe cohort quality	1, 2, 3	1		
Environmental impact	1, 2, 3	3		
Spill containment ability	1, 2, 3	3		
Damage risk from civil works	1, 2, 3	2		
Existence of occluded air pockets along the length of pipeline			1, 2, 3	3
Pressure class (surrogate for pipe wall thickness)			1, 2, 3	2
External soil environment			1, 2, 3	1
Environmental impact			1, 2, 3	3
Spill containment ability			1, 2, 3	3
Damage risk from civil works			1, 2, 3	1
Air release valve(s) condition			1, 2, 3	3

* Material risk scale: 1 – Favourable; 2 – Intermediate; 3 - Unfavourable
* Risk ranking of criteria: 1 - Low importance; 2 = Intermediate importance; 3 = High importance

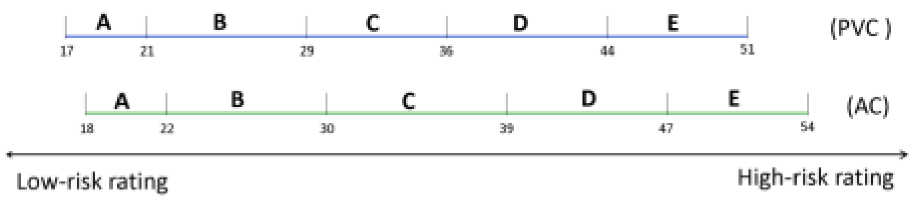

Figure 1. Overall risk rating scheme for a) PVC and b) AC sewer rising mains

3. CAPTURING SEMANTICS WITH ONTOLOGIES

Ontologies allow definitions about the domain and application to be captured explicitly and used consistently. Figure 2 shows the ontology modules used to support the capture of semantic description and annotation of sensors, observations, events, domain concepts and domain rules. The ***general information model*** is based around the

SSN ontology (shown in orange) extended with event and quantity semantics (shown in blue) as presented in [11]. It is extended with a ***water domain model*** (shown in green) and an ***application specific model*** (shown in pale orange).

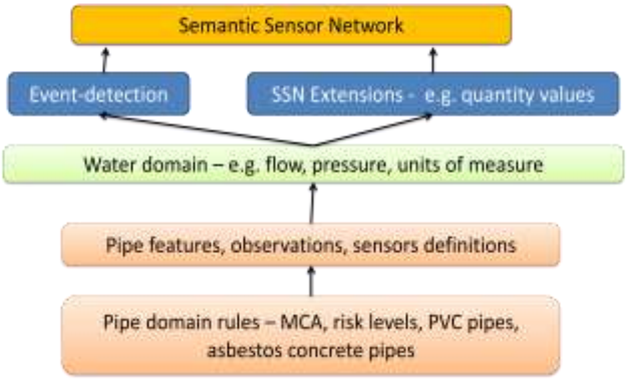

Figure 2. General, water domain and application ontology modules

Figure 3 illustrates the extensions made for this application respectively – specifically to model the features of interest, related observation types and sensor classifications. Using OWL descriptions, appropriate information about pipe anomalies in sewer rising mains when they exceed a threshold value as presented in Section 2, can be described. An example is given below using the Turtle syntax (see Figure 4).

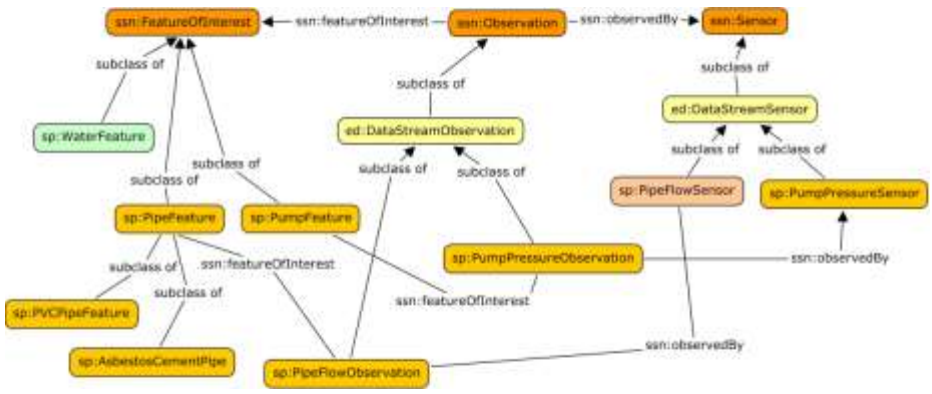

Figure 3. Application specific model for capturing pipe and pump observations

```
:uw_rule1      a       ed:ValueConstraintEventRule ;
    rdfs:label "flow, pipe  1, pipe flow sensor a, > 100 l/s”;
    ssn:featureOfInterest :Pipe1 ;  ssn:observedBy             :sewerpipea ;
    ssn:observedProperty       uwda-pipe-sensing:flow ;
    ed:hasValueConstraint      :valueConstraint1         .
```

Figure 4. Example Event rule definition

We capture the risk criteria of the Pipe Feature types (also presented in Section 2) using OWL property descriptions i.e. PVC and AC Pipe feature classes, with the appropriate risk criteria values. An example is given below using the Turtle syntax.

```
<http://waterinformatics-ext1-cdc.it.csiro.au/ld/resource/Pipe2>
      a                  uwda-pipe-sensing:PVCPipeFeature ;
      rdfs:label         "PVC Pipe 2” ;
      uwda-pipe-sensing:damageRiskFromCivilWorks “1”^^xsd:int ;
      uwda-pipe-sensing:environmentalImpactRisk “3”^^xsd:int  ;
      uwda-pipe-sensing:hasPreviousBurstHistory
        uwda-pipe-sensing:BurstEvent2 , uwda-pipe-sensing:BurstEvent1 ,
        uwda-pipe-sensing:BurstEvent3 ;
      uwda-pipe-sensing:pipeInstallationDate  "2000-01-01"^^xsd:date ;
      uwda-pipe-sensing:resistanceToSurgePressures “3”^^xsd:int  ;
      uwda-pipe-sensing:spillContainmentAbility    “3”^^xsd:int  ;
      geo:lat            "-37.948835"^^xsd:string ;
      geo:long           "145.042849"^^xsd:string                 .
```

Figure 5. Example Pipe Feature individual description for Pipe 2

We also capture other knowledge using SPIN rules [6] such as the risk rating scheme for both PVC and AC Pipe feature classes introduced in Section 2. SPIN is a framework that utilizes the SPARQL query language to help define constraints and inference rules. Several have been defined, but we give an example SPIN rule below for evaluating overall risk levels for the PVCPipeFeature class.

```
CONSTRUCT {  ?this uwda-domain-constraints:riskLevel ?riskLevel . }
WHERE {
   ?this uwda-domain-constraints:totalRiskScore ?score .
   OPTIONAL {
      BIND (<http://waterinformatics-ext1-cdc.it.csiro.au/ld/resource/RiskLevel_E> AS ?riskLevel) .
      FILTER (?score > 43)    } .
   OPTIONAL {
      BIND (<http://waterinformatics-ext1-cdc.it.csiro.au/ld/resource/RiskLevel_D> AS ?riskLevel) .
      FILTER ((?score > 35) && (?score <= 43))     } .
   OPTIONAL {
      BIND (<http://waterinformatics-ext1-cdc.it.csiro.au/ld/resource/RiskLevel_C> AS ?riskLevel) .
      FILTER ((?score > 28) && (?score <= 35))     } .
   OPTIONAL {
      BIND (<http://waterinformatics-ext1-cdc.it.csiro.au/ld/resource/RiskLevel_B> AS ?riskLevel) .
      FILTER ((?score > 20) && (?score <= 28))     } .
   OPTIONAL {
      BIND (<http://waterinformatics-ext1-cdc.it.csiro.au/ld/resource/RiskLevel_A> AS ?riskLevel) .
      FILTER (?score <= 20)    }
}
```

Figure 6. Example SPIN rule

Execution of the SPIN rules results in additional annotations to the respective OWL individuals with the appropriate risk levels, e.g. *Risk rating A*. This is then used as contextual information and decision support for evaluating the relative importance of each pipe anomaly detected in the event detection system. An example of the generated triples from SPIN rules are shown below.

```
:Pipe2
  uwda-pipe-constraints:age                               “13”^^xsd:int  ;
  uwda-pipe-constraints:ageRiskLevel                      “3”^^xsd:int   ;
  uwda-pipe-constraints:priorPipeBurstHistoryRisk         “3”^^xsd:int   ;
  uwda-pipe-constraints:totalRiskScore                    “47”^^xsd:int  ;
  uwda-pipe-constraints:riskLevel
      <http://waterinformatics-ext1-cdc.it.csiro.au/ld/resource/RiskLevel_E> .
```

Figure 7. Example set of RDF statements "inferred" from SPIN rules

These domain and application knowledge is stored in a triple store as part of the event detection system, which is described further in the Section 3.

3. EVENT DETECTION SYSTEM IMPLEMENTATION

In this section, we describe the *event detection system* implementation for automated pipe failure detection (see Figure 8). The backend system is consists of a number of components. GSN is used as the sensor middleware and provides interfaces to the underlying sensor data, which may be physical sensors, or data streams from other software components. In this application, these are pipe flow observations.

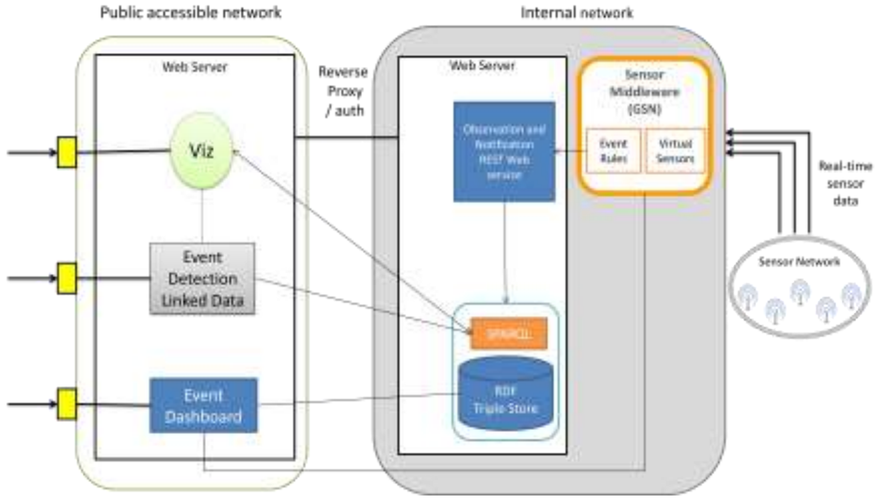

Figure 8. Event detection system component diagram

The Observation and Notification REST Web service provides the interfaces for creating RDF descriptions of observations and notifications, based on the semantics and resources defined in the ontologies presented in Section 3. The ontologies and the *inferred* statements generated from the SPIN rules are stored in the RDF Triple Store shown in shown in Figure 8. As part of the creation of observations and notification statements, the RESTful web service adds links to related resource descriptions, such as the event rule description, the sensor, feature of interest (e.g. Pipe features and its risk levels) and its geo-location. These generated observations and any triggered event notifications are also stored in the RDF Triple Store.

At the front end, separate client applications can then interface with the backend system to provide multiple views. In this paper, we focus on the Event Detection

Linked interface, which uses the Epimorphics Linked Data API (ELDA)[1] for providing human readable and machine-readable views of notifications and observations descriptions as well as related RDF resources[2]. Figure 9 shows the human readable view of an event notification, however, using this interface, other machine-readable views of the same resource are available e.g. RDF and JSON. An example of the RDF view, expressed in Turtle syntax, is given in Figure 10 (note this is not the actual location of the rising main).

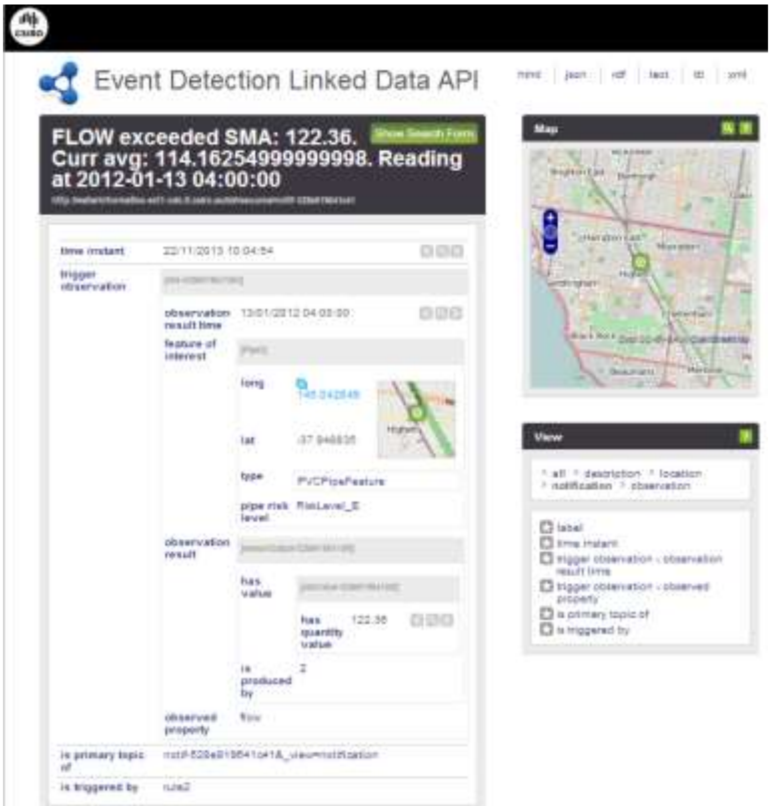

Figure 9. Example notification description using the Event detection linked data API

```
:notif-528e919641c41
    rdfs:label  "FLOW exceeded. Reading at 2012-01-13 04:00:00" ;
        ed:isTriggeredBy     event-rule:rule2 ;
        ed:timeInstant       "2013-11-22T10:04:54+11:00"^^xsd:dateTime ;
        ed:triggerObservation  :obs-528e919641b63  .
:obs-528e919641b63    ssn:featureOfInterest      :Pipe2 ;
   ssn:observationResult     :sensorOutput-528e919641bf8 ;
   ssn:observationResultTime  "2012-01-13T04:00:00Z"^^xsd:dateTime ;
   ssn:observedProperty       uwda-pipe-sensing:flow .
```

Figure 10. Example RDF description of a notification and related observation

[1] See http://www.epimorphics.com/web/tools/elda.html
[2] See http://waterinformatics-ext1-cdc.it.csiro.au/elda/event/list/notification

5. CONCLUSION AND FUTURE WORK

In this paper, we presented an *event detection system* using linked data approaches to address challenges in the domain to be addressed, specifically for automating pipe failure detection. The system extends an existing design for ontology-based approach for complex event processing with linked data approaches for structuring observations and event notification descriptions. Each notification is linked to other related sensor, observation, and domain concepts (such as pipe characteristics and risk levels) to provide contextual information. These semantic descriptions are defined based on our extensions to ontologies that were presented in [11]. We demonstrated how pipe sensor data that organisations already gather in business-as-usual practices can be repurposed for automated pipe failure detection using the *event detection system*. We showed that ontologies can be used to capture domain expertise and pipe characteristics for use in the event detection system, that is, semantics for pipe features and their characteristics are captured in domain and application ontology modules using the general ontology modules presented in this paper. The pipe risk constraints and the rating scheme were encoded as SPIN rules which allowed risk levels to be generated for each Pipe Feature individual defined in the ontologies.

6. REFERENCES

[1] K. Aberer, M. Hauswirth, and A. Salehi. A middleware for fast and flexible sensor network deployment. In *Proc. 32nd Intl. Conf. Very Large Data bases*, VLDB ’06, pp. 1199–1202, 2006.

[2] M. Compton, P. Barnaghi, L. Bermudez, R. Garcia-Castro, et al. The SSN Ontology of the W3C Semantic Sensor Network Incubator Group. *Web Semantics: Science, Services and Agents on the World Wide Web*, 17:25–32, Dec 2012.

[3] P. Davis, D. De Silva, D. Marlow, M. Moglia, S. Gould, and S. Burn. Failure prediction and optimal scheduling of replacements in asbestos cement water pipes. *Water Supply Research and Technology-Aqua*, 57(4):239–252, 2008.

[4] P. Davis, E. Sullivan, D. Marlow, and D. Marney. A selection framework for infrastructure condition monitoring technologies in water and wastewater networks. *Expert Systems with Applications*, 40(6):1947–1958, 2013.

[5] S. J. F. Gould and P. Davis. PVC rising main failure analysis by fractography and investigation of operational data. In *Proc.1st Intl.Conf. Infrastructure Failures and Consequences (ICIFC)*, Melbourne, Australia, July 2014. RMIT.

[6] H. Knublauch. Sparql inferencing notation (SPIN). http://spinrdf.org (Accessed Feb. 2014).

[7] D. Marney and A. Sharma. The application and utility of “smarts” for monitoring water and its infrastructure. *Water Journal*, 39:2, 2012.

[8] Saul A.J. Shepherd, W.J. and D. Hanson. A case study of long term sewer hydraulic modelling. In *6th Intl. Conf. Sewer Processes and Networks (SPN)*, Qld, Australia, Nov. 2010.

[9] K. Taylor and L. Leidinger. Ontology-driven complex event processing in heterogeneous sensor networks. In *Proc. 8th Extended Semantic Web Conference*, pp. 285–299, Crete, Greece, May 2011. Springer.

[10] J. Yu, K. Taylor, and B. Sherman. Ontology-driven complex event processing for real-time algal bloom detection. In *Proc. 7th Australasian Ontology Workshop*, Vol.132 *CRPIT*, pp. 35–36. ACS Inc., 2011.

[11] J. Yu and K. Taylor. Event dashboard: Capturing user-defined semantics events for event detection over real-time sensor data. In *Proc. Intl. Workshop on Semantic Sensor Networks*, CEUR-WS Vol. 1063, pp. 35–50, October 2013.