Smart Water Management: An Ontology-Driven Context-Aware IoT Application

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Abstract. This paper presents a context-aware ontology driven approach to water resource management in smart cities for providing adequate water supply to the citizens. The appropriate management of water requires exploitation of efficient action plan to review the prevailing causes of water shortage in a geospatial environment. This involves analysis of historical and real-time water specific information captured through heterogeneous sensors. Since the gathered contextual data is available in different formats so interoperability across diverse data requires converting it into a common perceivable RDF format. As the perceptual model of the Smart Water domain comprises of observable media properties of the concepts so to achieve context-aware data fusion we have employed multimedia ontology based semantic mapping. The multimedia ontology encoded in Multimedia Web Ontology Language (MOWL) forms the core of our IoT based smart water application. It supports Dynamic Bayesian Network based probabilistic reasoning to predict the changing situations in a real-time irregular environment patterns. Ultimately, the paper presents a context-aware approach to deal with uncertainties in water resource in the face of environment variability and offer timely conveyance to water authorities by circulating warnings via text-messages or emails. To illustrate the usability of the presented approach we have utilized the online available sample water data-sets.

1 Introduction

Water is a vital natural resource which drives our ecosystem but rise in population growth and urbanization has put a limit to the water supply and even led to water crisis. In these conditions, successful management of water resources requires deploying IoT technologies and utilizing efficient planning methodologies to predict causes responsible for shortage of water in a smart city. This will provide an accurate knowledge of the available water resources to meet the competing demands. The knowledge about the water domain constitutes of water quantity, it's quality etc. which is time-consuming and expensive to analyze using existing approaches. Moreover, the present water management system such as ICT lacks inter-operability standards and results in low monitoring efficacy. Thus, use of IoT technologies [2] such as smart water meters, soil sensors

B.U. Shankar et al. (Eds.): PReMI 2017, LNCS 10597, pp. 639–646, 2017.
https://doi.org/10.1007/978-3-319-69900-4_81

to estimate moisture or chemical substance in the ground area etc. offers significant tracking capabilities to manage the issues generated as a consequence of lack of available water resources [1]. The data captured by the assortment of devices are of different media formats so to enable integration and for conceptual inter-operability a formal semantic representation is required. The author in [4] proposed semantic based knowledge management system for water flow and quality modeling. The work in [5] presents a concept which combines actors, hydro logic concepts and relationships among them to offer a unified approach to manage water related issues. The authors in [8] presented a concept of linked water data to create an integrated graph of information required for managing water effectively. These systems failed to reason with uncertainties involved in multimedia observations which impedes the desired vision. So, a multimedia ontology encoded in MOWL [3] would be useful for flexible media data representation. MOWL allows to represent the data with semantic properties and supports Dynamic Bayesian Networks (DBN) [7] as a probabilistic reasoning model that captures the dependencies among variables and utilizes context developed over time [6]. In smart water scenario the level of uncertainty originate from various knowledge perspectives such as unpredictable climate variation, water contamination, water pH etc. which involves ambiguities. To understand the environment and water availability over a range of temporal scales the pre-requisite context information is obtained through intelligent devices. The proposed framework utilizes this information to achieve context-aware semantic mapping so as to support data fusion and automatic interpretation of the context. Further, DBN based reasoning capabilities of MOWL helps to analyze the source of water and predict the uncertain environmental situation responsible for water shortage in the specific context. The predictability of these situations in real-time will help to provide guidance to the local water authorities about lower water supply under which management can be performed.

2 Multimedia Ontology in Smart Water Domain

In an IoT environment, use of semantic web technologies provides a common platform for knowledge access and interchange by minimizing the semantic heterogeneity that exists between various devices. The existing semantic approaches such as OWL supports conceptual modelling but fails to interpret the perceptual world due to the semantic gap that exists between the perceptual media features and the real world. The perceptual modelling comprises of observable media properties of the concepts which are useful for concept recognition or semantic interpretation of multimedia documents. So, MOWL [3] can be used as an alternate ontology representation language which associate different media features in different type of media format and at different levels of abstraction with the concepts. MOWL assumes causal model of world and supports probabilistic association of media properties with the domain concepts. MOWL based knowledge representation graph is composed of the following parameters:

(i) $\{C, M_p, M_e\}$ where, C is the set of concepts, M_p and M_e are the set of media patterns and media examples respectively; (ii) relation $\{R_p, R_h\}$ which organizes concepts and properties in a hierarchical structure, where R_p specifies the propagation of media properties between a concept and its related concepts while R_h represents the set of hierarchy among the concepts.

In smart water domain, knowledge representation in MOWL consists of water-specific concepts, with its expected media properties to deal with inherent uncertainties in observation of media patterns by setting Conditional Probability Tables (CPT's). The sensory inputs such as water-pH reading, water flow reading etc. forms the basis of context which are modeled as media patterns in the ontology. The snippet ontology using MOWL constructs shown in Fig. 1 specifies event and device ontology. Event ontology incorporates set of activities such as river-level, ground water-level etc. at a given location and time while device ontology describes the devices which are capable of monitoring objects. In figure, ellipse nodes represent domain concepts while rectangular nodes represent their observable media properties which are linked through edges. The concept is recognized on the basis of gathered evidences as a result of detection of expected media patterns. The vision to build context-aware services by aggregating knowledge from IoT devices is achieved by using DBN.

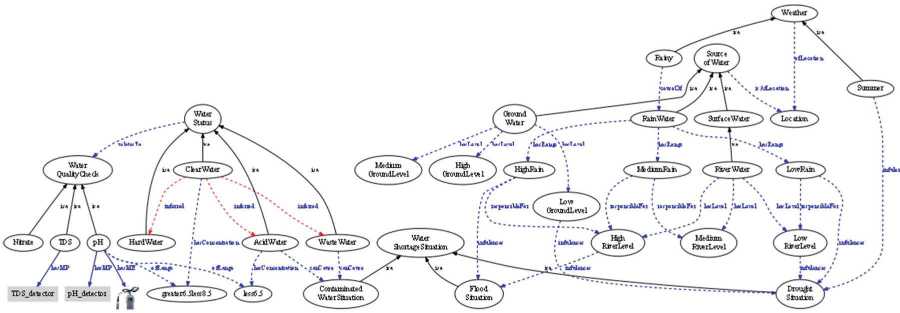

Fig. 1. Snippet ontology in smart water application

2.1 Dynamic Context-Aware Situation Modelling

Figure 2 depicts a MOWL based DBN model for context-aware situation tracking in real-time. It consists of sensor information, context state and situation state at time interval say t_1 and t_2. The situations at time slice t1 to t2 are linked through transition links (red color). The reasoning process derives a sub-graph Observation Model (OM), at each time step for concept recognition which contains the situation hierarchy and other concepts related to situation, thus enabling the modelling of dynamic situation. Here, the belief at each level is computed by considering current evidences along with prior inferred situations. The state transitions at different time stamps (say t_1 to t_2) allows to deal with changing situations in the dynamic environment. The DBN formulation on the sequence of S states and E sensor observations is as:

$P(S,E) = \prod_{t=1}^{T-1} P(S_t|S_{t-1}) \prod_{t=0}^{T-1} P(E_t|S_t)\ P(S_0)$; where $P(S_0)$ specifies likelihood of initial state, $P(S_t|S_{t-1})$ describes temporal state transitions and $P(E_t|S_t)$ specifies probability distribution for sensor observations.

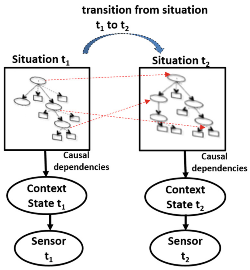

Fig. 2. DBN based situation evolution (Color figure online)

3 Ontology Based Smart Water Architecture

The management of water resource is an uncertain and dynamically complex problem. An ontology-driven smart water framework in context-aware perspective requires pre-requisite information about the change in climate, environment conditions, water quality etc. to understand the water availability over a range of temporal scales. The multimedia ontology based architecture as shown in Fig. 3 consists of the following main elements:

- **Data-acquisition Layer:** This layer is responsible for monitoring and acquiring data from multiple sources using IoT devices. The sensors and environment indicators such as smart water meters, climate sensors, water-level sensors etc. helps to sense the information of the water quality, its surroundings and communicates the collected data over a network (such as 3G, Wi-Fi etc.) for analysis. The transferred data is of different formats so to produce accurate and complete information, this low-level context information is converted into a higher-level context using a common understandable RDF format discussed in next phase.
- **Context-aware Service Layer:** The middle-tier operates in a bi-directional mode which integrates disparate sensor data to establish a common understanding of context by employing semantic web technologies. This context data serves as key source of information for inferencing and predicting dynamic situations. We have chosen MOWL for knowledge representation in smart water domain. It allows for semantic interpretation of media documents and deals with uncertainties involved in the media manifestations. MOWL uses DBN based probabilistic reasoning to track situations in a dynamic world which is passed on to the next phase depending on which appropriate recommendations are given.

– **Application Layer:** This phase ensures clear and accurate presentation, visualization of resulting information to the users. As the proof-of-concept in the Smart Water application, the derived knowledge from the previous layer is utilized to give appropriate recommendations or warnings to the water authorities to take suitable actions in water deficit areas. The warnings can be disseminated through via e-mail, text messages thus, offering optimum water supply to the users.

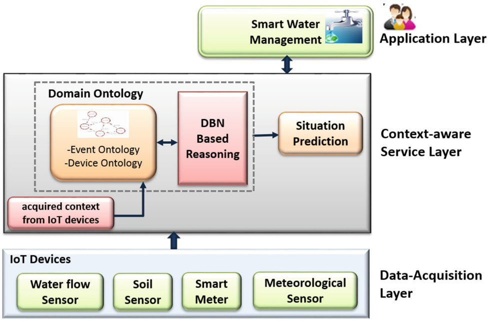

Fig. 3. Smart water architecture

4 Problem Formulation

The outdated water-infrastructure, situations such as drought, flood etc. caused due to randomly occurring climate and monsoon patterns, etc. has led to the emergence of water crisis in urban areas. Therefore, proper water management is required to overcome the imbalances caused by shortage of water. The real-time scenario which addresses the need for proper water management and planning is for example, the two consecutive droughts in Latur Maharashtra, 2016 caused acute water scarcity in the Marathwada region. The absence of timely guidance about the monsoon failure and thus, a lack of management to deal water crisis resulted in death of several farmers. So as a solution to address these shortfalls, we have come up with MOWL based inferential reasoning process in IoT domain. This allows to consider the historical data or past actions along with real-time data to assess the situation responsible for water scarcity and provide timely assistance to water authorities to take immediate actions.

4.1 Theoretical Analysis

This section allows to observe water-specific parameters collected from the distributed sensors so as to provide essential information about the quality of water and take effective decisions based on it. We referred to water quality data available on the site[1] (Avalon Peninsula) and collected samples of Faridabad city

[1] http://www.mae.gov.nl.ca/wrmd/ADRS/v6/Graphs_List.asp.

for analysis and assessment of the situation causing shortage of water. The water specific attributes pertaining to the individual datasets are mapped to the ontology concepts leading to updated posterior probabilities in the network. The associated semantics (such as perceiving different water-concentrations and indicators to classify water as clear, hard or acidic) and the dynamic reasoning process helped to infer the real-time situation. For instance, in the former data set the context state *ClearWater* at very time step lead to *NormalWaterSituation* with the probability value of 0.78 while in latter the context state *HardWater* pointed to *ContaminatedWaterSituation* with probability 0.74.

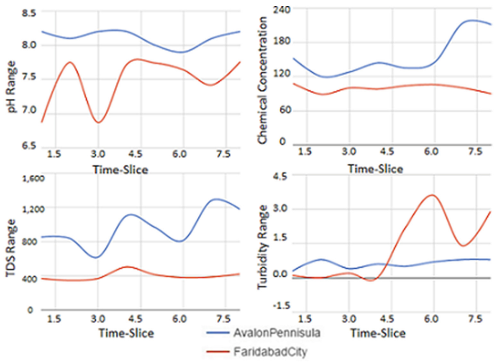

Fig. 4. Plot of few water parameters

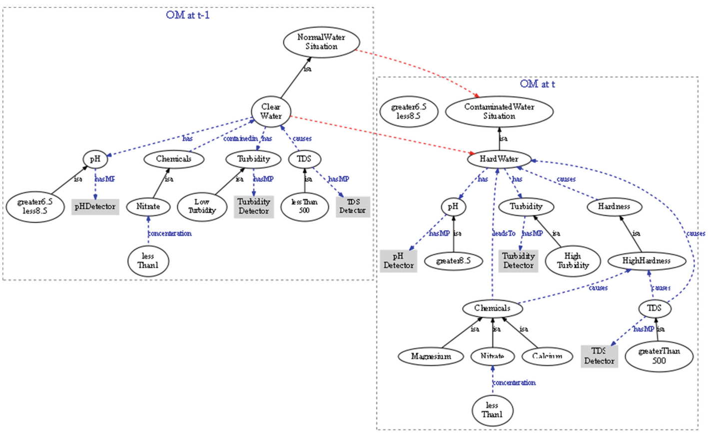

Fig. 5. MOWL based situation tracking

As there was not much variation among the pH values and other water concentrations so at every time stamp the same situations got recognized in both the scenarios. To demonstrate the real time state transitions and dynamicity of the framework for example: *clear water getting contaminated due to exposure to chemical concentrations* we combined few samples from both of the datasets to form a new relevant dataset. Some of the parameters corresponding to the dataset are plotted as shown in Fig. 4. The transition from *ClearWater* to *HardWater* is represented through transition links in the ontology. The use of transition links in the MOWL support setting of prior conditional probabilities for switching between dynamic situations. DBN depicted in Fig. 5 extrapolate results at time step *t-1* and *t* to track the current situation responsible for water crisis. To illustrate the process, let the prior probability of ClearWater and HardWater based on the transition links be P(ClearWater | HighTDS, HighChemicalConcentration, HighTurbidity) = 0.15, P(HardWater | ClearWater, HighTDS, HighChemicalConcentration, HighTurbidity) = 0.95. Following DBN based inferencing scheme, the updated posterior probability obtained for states P(ClearWater) = 0.34 and P(HardWater) = 0.76 which leads to P(NormalWaterSituation) = 0.26 and P(ContaminatedWaterSituation) = 0.68, and contributes to higher possibility of *ContaminatedWaterSituation* over *NormalWaterSituation*. The use of standard Bayesian Network approach would not have been sufficient enough to capture these dynamic transitions. Figure 6 plots the probability estimates for *ContaminatedWaterSituation* and *NormalWaterSituation*. The results shows the abrupt rise in ContaminatedWaterSituation after three time slices due to the presence of evidences affecting water quality based on which alerts can be given to water authorities to take corrective actions for hygienic water-supply, which shows efficacy of our approach.

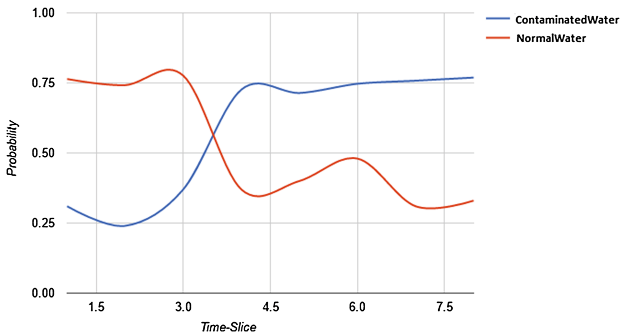

Fig. 6. Probability variation between NormalWaterSituation and ContaminatedWaterSituation

5 Conclusion

We have presented a novel semantic based context-aware framework which can dynamically acquire a range of water-specific information in an IoT environment.

This information constitutes context required for understanding the causal relationships among the concepts and to predict changing situations. The envisioned smart water architecture utilizes MOWL to enable integration and semantic interpretation of complex sensory data. MOWL inferencing with DBN helps to tackle the uncertainties involved in water domain such as change in climate which highly impacts the water service. The proposed approach would assist urban water authorities to grapple with shortfalls causing chronic water crisis under which water management is possible.

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