Swarm-based semantic fuzzy reasoning for Situation Awareness Computing

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Abstract—Situation awareness computing employs sensor networks to collect large amounts of heterogeneous data in different and complex environments. The rapid development and deployment of sensor technology stress the problem related to the availability of too much and heterogeneous data. Last trend emphasizes the semantic annotation of acquired sensor data. Semantic sensor data provides machine understandable contextual information. In particular, the availability of semantic sensor data allows situation awareness in several application domains. This paper introduces a swarm-based approach to semantic web reasoning in order to identify situations. On one hand, fuzzy control has been employed in order to face with uncertainty of happening situations. On the other hand, Situation Theory has been used in order to model situation awareness. A multi agent swarm architecture enables to monitor complex environments by using spatially distributed autonomous sensors. An application scenario for bank intrusion detection has been described.

Keywords-component; situation awareness, semantic sensor web; semantic web; fuzzy control; swarm intelligence.

I. INTRODUCTION

Situational Computing paradigm is a pervasive computing paradigm where a situation aware application has the ability to perceive and comprehend the environment. The acquisition of context information is usually based on sensor data that are hardly ever perfect or certain, especially within unsupervised environments. Furthermore, theories and models proposed so far for representing and managing sensor data are mostly aimed at ensuring semantics-aware interoperability of the sensor infrastructure, leaving uncertainty management aside.

Sensor technology involves several types of sensors (e.g., thermostats, pressure gauges, pollution detectors, cameras, microphones, glucose sensors, etc.) that enable to monitor cities, atmosphere, our body, and so on. Furthermore recently sensor technology offers cheap and energy-efficient hardware for data sensing. Deployment of (wireless) sensor and actuator networks makes it possible to monitor physical phenomena and reason on obtained information. It is possible to use sensor networks to detect and identify a multitude of observations, from simple phenomena to complex events and situations. Nevertheless, the lack of integration and communication between sensor networks often isolates important data streams and intensifies the existing problem of too much data and not enough knowledge. Specifically, quality and efficiency of reasoning on sensor data is closely related to the representation, sharing and management of observations.

Over the past few years, many research works address developing of large scale sensor networks, such as SensorWeb 1. Open Geospatial Consortium (OGC) has proposed Sensor Model Language (SensorML) that is an XML-based standard that lacks of semantic model. Recently many research works address this problem by encouraging development of sensor and actuator data representation using semantic technologies [1], such as: Semantic Sensor Web [2], OntoSensor [3], etc. Semantic web technologies enrich sensor data with semantic annotations. In particular, semantic formalisms acquire machine understandable contextual information. As highlighted in [4], emerging challenge is related to perform reasoning over the sensor observation and measurement and linked data 2 to detect emerging situation.

The paper aim is closely related to define a framework that exploits availability of semantic sensor data in order to identify relevant situations in several dynamic environments. Specifically, this work focuses on the problem of distributed reasoning on semantic data and enhances description logic reasoner by exploiting situation theory and fuzzy theory in order to approximate relevant situations. In [5] the authors emphasize the role of upper ontology Fuzzy Situation Theory Ontology (FSTO) that handles vagueness and uncertainty modeling in situation theory. On the other hand, the present work stresses the evaluation of fuzzy controls on semantic data, in order to forecast emerging situations. Fuzzy controls are modeled according to Fuzzy Markup Language (FML) [7], a novel language useful for modeling advanced fuzzy systems by means of a structural and taxonomic approach that improves fuzzy systems design in terms of transparency and reliability.

Let us assume that sensor data are represented according to Semantic Sensor Web [2]. The main contribution of the proposed work is the application of a synergic approach based on swarm intelligence, situation theory and fuzzy

2 http://www.w3.org/DesignIssues/LinkedData.html
control theory in order to distribute reasoning on semantic sensor data and to push out forecasting of emerging situations. In particular, we provide a swarm based semantic web reasoning engine in which simple agents (swarm entities) are able to exploit fuzzy control. Specifically, the network on which each agent acts is represented by RDF (Resource Description Framework [6]) graph of situations semantic data model.

The paper is organized as follows: Section II presents some related works available in literature; Section III defines the swarm-based framework and workflow for supporting semantic fuzzy reasoning on situations data. Then, Section IV describes an illustrative scenario aimed to approximate knowledge about bank intrusion detection and to support security operators. Finally, conclusions and future works close the paper.

II. RELATED WORKS

Many situation models [8] appear in the situation awareness literature. Certain models are capable of reasoning about situation knowledge [9]. Using propositional logic, the authors in [10] describe situations as concepts, consider the compatibility relations among situations, and, apply rules in order to infer the situation of an entity. The work discussed in [11] deals with consistent situations with respect to situation calculus axioms. In addition, in [12] the authors discussed about core ontologies representing situations, but with lack of enhanced semantics, thus, restricted knowledge reasoning. Such models focus on default reasoning that results in a crisp subsumption of unclassified situations. Furthermore, the authors in [13] modeled the user context as situations. They proposed a method to retrieve such situational knowledge by applying a logical matching method against system and user expectations related to current/future situations. Situation conceptual modeling has also been attempted in several information models, especially in the era of situation awareness and situation calculus. Significant work related to conceptual Description Logics, situational modeling and reasoning has been reported by the authors in [14]. Finally, the authors in [15] deal with situational context recognition through data fusion techniques. On the other hand, situation semantic models are often unable to deal with many cases of real world, where information is vague in meaning; so, in order to deal with this issue in [16] the authors introduced OWL-FC in order to represent fuzzy controllers and enable their discovery and execution by means of Description Logic constructs. This work exploits OWL-FC in order to semantically specify controllers.

Furthermore, to obtain better performance and have higher fault tolerance in sensor observation errors, swarming agents in sensor networks may be used for data acquisition, data fusion and control applications. The swarm intelligence design approach adapts robust, self-organizing coordination mechanisms observed in distributed natural systems (e.g., social insect colonies) to engineered systems. Specifically, [17] presents a swarming agent architecture for distributed pattern-detection and classification.

Again, [19] describes a swarm-based fuzzy logic control mobile sensor network for collaboratively locating the hazardous contaminants in an unknown large-scale area. Each node’s fuzzy logic control can determine its next optimal deployment location. [18] introduces an adaptive web search system, based on Ant System computational paradigm. The system is composed of agents that cooperate to adapt to the environment and to the user information needs, in order to increase the quality of retrieved information. Furthermore, in [20] the authors have presented a novel method for Semantic Web reasoning based on Swarm Intelligence. The major feature of this idea is that many light-weight autonomous agents collectively calculate the semantic closure of RDF(S) graphs by traversing the graphs, and apply reasoning rules to the nodes they are currently located on. The advantage of this approach is its adaptiveness and its capability to deal with distributed data from dynamic sources.

Analogously with [20], this paper proposes a framework that applies swarm intelligence to improve distributed semantic fuzzy reasoning on situations data. Specifically, swarm intelligence, situation theory and fuzzy control are exploited to make reasoning on semantic situations data in order to push out knowledge and forecast emerging situation.

III. SWARM-BASED FRAMEWORK

A. Architectural Overview

In order to address goals of this work a multi agent architecture has been instantiated. Figure 1 gives an outlook about architectural components, on the left side, and of the workflow, on the right side.

In particular, coordination of agents is addressed with stigmergetic interactions. In other words, agents move and dynamically organize themselves by using artificial pheromones on RDF graph (modeled according to FSTO). The RDF graph is situation data model as the spatial structure of the pheromone infrastructure. Indeed, an RDF node is interpreted as a location where agents may deposit or sense pheromones and where the infrastructure manipulates local concentrations in each node. Therefore these agents in the proposed framework coordinate their activity and communicate their results through markers in a shared dynamic environment.

The architecture is based on large populations of mobile agents that are equipped with specific tasks. We distinguish:

- **Infon Manager Agent**, which acquires semantically annotated sensor data and builds information about a situation in terms of infons, that is, according to FSTO. Infons are added to situations model on which Fuzzy Reasoning Agents perform reasoning.
- **Node Agent**, which provides infrastructure services in order to manage digital pheromone properties
(i.e., concentration, propagation and evaporation) on each location (i.e., the RDF node). These agents implement the local pheromone dynamics, provide topological information and manage the local interactions among neighbor agents.

Figure 1. Architectural components (left side) and phases of the workflow (right side).

- **Fuzzy Reasoning Agent**, which faces the problem of inferring relevant situations by browsing the RDF graph consisting of information about situations. These agents add inferred situations to semantic data model according to their classification schema (i.e., fuzzy control). So, they influence: a) where to focus the search; and b) what to declare as relevant situation or part of it. Furthermore, a population of Fuzzy Reasoning Agent could be deployed at any time, for instance to add more classification schemes according to different situations.

- **Situation Notifier Agent**, migrates on each node and acquires situations classification by detecting pheromone released by Fuzzy Reasoning Agents. These agents provide notifications as stated by a situation pattern and a specific threshold, configured in order to choose which classified situation should be notified. Similarly to Fuzzy Reasoning Agent, Situation Notifier Agent could be deployed at any time, for instance to add more notification schemes according to different situations.

**B. Workflow**

The main goal here is to define methodology to reason on RDF graph in order to support situation awareness. In particular, reasoning is essentially performed by evaluating fuzzy classification based on fuzzy control theory.

The workflow of the proposed approach is essentially composed of four main phases: Semantic Data Sensing, Situation Data Semantic Modeling, Swarm-based Fuzzy Reasoning, Relevant Situation Notification. On the right side of Figure 1 is sketched execution of this workflow. Next subsections detail each activity.

1) **Semantic Data Sensing**

Extracting useful knowledge from raw sensor data is not a trivial task. Conventional data analysis tools might not be suitable for handling the massive quantity, high dimensionality, and distributed nature of the data. The goal of this phase of the workflow is therefore to provide sensor data with knowledge useful for their interpretation and make this knowledge available for further processing aimed to infer new information.

The activity of Semantic Data Sensing concerns the acquisition of data from different data sources (e.g. thermostats, cameras, microphones, position sensors, etc). Data acquisition begins with the physical phenomenon or physical property to be measured. Examples of this include temperature, light intensity, gas pressure, fluid flow, location and force. Regardless of the type of physical property to be measured, sensors transform the physical state that is to be measured into a unified form that can be sampled by a data acquisition system. The ability of this activity to measure different properties depends on having sensors that are suited to detect the various properties to be measured.
In this approach the authors assume that each measurement provided by sensor is semantically annotated. In particular, each measurement is supposed to have spatial, temporal and thematic dimensions [2].

2) Situation Data Semantic Modeling

This activity concerns the acquisition and comprehension by Infon Manager Agents of semantically annotated sensor data and the subsequent building of infons about situations according to FSTO. Let’s remember that in FSTO, an infon \( \sigma_i \) supporting a situation \( s_j \) is written as:

\[
\sigma_{i,s_j} \equiv << R_i, a_1, a_2, \ldots, a_n, \tau_{\sigma_{i,s_j}} >>
\]

where \( R_i(a_1, a_2, \ldots, a_n) \) is \( \tau_{\sigma_{i,s_j}} \) in \( s_j \), with \( \tau_{\sigma_{i,s_j}} \) stating that \( R_i(a_1, a_2, \ldots, a_n) \) is \( \tau_{\sigma_{i,s_j}} \) in \( s_j \), and \( \tau_{\sigma_{i,s_j}} \) is written as:

\[
\tau_{\sigma_{i,s_j}}(R_i(a_1, a_2, \ldots, a_n)) = \sigma_{i,s_j}(R_i(a_1, a_2, \ldots, a_n))
\]

involving \textit{true} and \textit{false} as primary terms (defined by membership functions), a finite number of hedges (i.e., \textit{more or less}, \textit{quite}, \textit{really}, \ldots) whose evaluation is performed by means of concentration and dilation, the connectives \textit{and} and \textit{or}, and the negation \textit{not}.

By adopting this modeling approach, the semantic of support proposition \( \models \) can be stated as:

\[
s_j \models \bigcup_{i} \{ \sigma_{i,s_j} \} \iff \forall i: R_i(a_1, a_2, \ldots, a_n) \text{ is } \tau_{\sigma_{i,s_j}}.
\]

Thus built infons are added to situations data model and are ready to be processed by reasoning agents.

3) Swarm-based Fuzzy Reasoning

Fuzzy reasoning on situations data represents a fundamental phase of the workflow. Specifically, the main aim is related to infer relevant situations from infons built in the previous phase. This result is exploited in order to notify, the occurrence or the likely occurrence of relevant situations, for instance by alerts or warning in emergency, security, strategic or military scenarios. In order to manage uncertainty, in distributed reasoning on situations, Fuzzy Control and Swarm Intelligence techniques are employed.

Swarm-based Fuzzy Reasoning activity involves a multi agent swarm behavior where the swarm entities are distributed among the nodes of an RDF graph representing situations data model.

The idea of this work is shown on the left side of Figure 2 and the first aspect to highlight is that when a swarm agent reaches a node, it chooses an ongoing path that starts at the current node. This decision can be taken based on pheromones that have been dropped by previous agents, or based on the infons, preferring infons which correspond to the pattern of the inference rule.

If the chosen infons match the agent’s pattern, the rule will be fired and the new inferred situation added to the graph.

Furthermore, in order to manage uncertainty and enable the prediction of situations Fuzzy Control is integrated in each reasoning agent, firstly in order to guide research focus and secondly to classify relevant pattern or part of them. Fuzzy Control is achieved thanks to a fuzzy-oriented markup language (FML) able to manage fuzzy concepts, fuzzy rules and fuzzy inference engine directly [7].

In particular, the interpretation (2) defines a modeled situation occurrence as the evaluation of a corresponding fuzzy control rule [21][22]:

\[
IF \ R_i(a_{i,1}, a_{i,2} \ldots, a_{i,n}) \text{ is } \tau_{\sigma_{i,s_j}}
\]

AND ...

\[
AND \ R_j(a_{j,1}, a_{j,2} \ldots, a_{j,n}) \text{ is } \tau_{\sigma_{j,s_j}} \then s_j \text{ is occurring,}
\]

where \( R_i(a_{i,1}, a_{i,2} \ldots, a_{i,n}) \) are fuzzy sets representing the input variables result from evaluation of degree whose objects \( a_{i,1}, a_{i,2} \ldots, a_{i,n} \) participate to relation \( R_i \).

Moreover, \( \tau_{\sigma_{i,s_j}} \) are membership functions assigned to corresponding input variables and \( s_j \) is the consequent function, that is, situation occurring degree. In the proposed work each Fuzzy Reasoning Agent evaluates its rules schema where each rule refers to degree of truth (or occurrence) of a situation. We observe that the defuzzified value deriving from the evaluation of fuzzy rule base in each Fuzzy Reasoning Agent may be interpreted as pheromone concentration of a specific flavour. Each Fuzzy Reasoning Agent population researches the maximum concentration of pheromone for one flavour (situation). In this way, the pheromone infrastructure is achieved where the property of concentration is obtained by the just described approach and the property of evaporation is determined by the temporal change of sensor detections. Therefore, Fuzzy Reasoning Agents moving as well as their pattern identification task are determined by pheromone concentration deriving from fuzzy control evaluation.

4) Relevant Situation Notification

Relevant Situation Notification activity concerns with the elicitation of relevant situations identified and added to situations model in the previous activity. In particular, this task is performed by Situation Notifier Agents which provide notifications in push-out mode. Specifically, in our approach the activity of situation notification consist of browsing RDF graph representing situations data model in order to filter identified situations according to a pattern and to a specific pheromone threshold. A sketch of this activity is shown on the right side of Figure 2 and it could be used to alert or warn decision makers through a user friendly front end.
I. CASE STUDY

To demonstrate the potential of the proposed approach, a simple scenario of intrusion detection in a video surveillance area of a bank has been implemented as described follow.

A. Application Scenario

Intrusion detection concerns the act of detecting actions that attempt to compromise the confidentiality, integrity or availability of a resource. The work considers bank intrusion as situation awareness scenario, in order to support bank security operators in the detection and/or prevention of theft and robbery. To evaluate the effectiveness of the proposed approach in scenarios detecting, we performed a series of experiments using intrusion detection datasets which supply four weeks emulation data. In the experiments the first week data do not contain any attack and the second week data contain 77 attack instances. The third week data contain no attack whereas fourth week data contain 123 attacks. Let’s assume for the application scenario that semantically annotated sensors acquired by Infon Manager agents are adequate to build information about situations.

Furthermore, let’s consider Bank Robbery Risk as relevant pattern to notify and consider Approaching To Bank Situation and Dangerous Person Situation as reasoning pattern. The aforementioned reasoning patterns as well as Bank Robbery Risk notification pattern are shown in Figure 4. Our Reasoning Agents search for nodes whose local data is significantly near to their patterns fulfillment (e.g., true values for infons). Thus, at each step from one node to the next a FuzzyReasoning Agent carries out its Fuzzy Control in order to measure the difference in the observed data and it assigns high evidence to a large differential. Local concentrations of pheromone, which the Fuzzy Reasoning Agents use to attract each other to potential patterns, are determined by defuzzification of fuzzy rules. In the experiments we employed 1000 Fuzzy Reasoning Agents and 500 Situation Notifier Agents. The non-propagating and evaporating pheromone indicate where the Fuzzy Reasoning Agents population believes the current patterns are. In the application scenario, we consider the concentration of two flavors of pheromone corresponding to Approaching To Bank Situation and Dangerous Person Situation, so our Situation Notifier Agents highlight only Bank Robbery Risk pattern.

B. Experimental Results

This section presents the performance results of our proposed approach. The experiment was performed within the MASON simulation environment, a multi-purpose simulation library for the Java programming language. The

3 http://cs.gmu.edu/~eclab/projects/mason/
test environment considers application scenario settings and the proposed Swarm-based Fuzzy Reasoning (SBFR) algorithm is compared with a Swarm-based Semantic Reasoning (SBSR) algorithm which only considers description logic inference to identify situation. Figure 4 highlights that approach based on fuzzy classification helps to approximate and recognize more relevant situations (i.e., patterns).

The retrieval performance is assessed in terms of precision and recall measures, considering the analysis through micro-average of the individual precision-recall curves [24]. Let \( S' = \{ S_1, S_2, ..., S_n \} \) be a set of \( n \) situation, \( D \) all the correct response to a specific situation. For each situation \( S_i \), we consider \( \lambda = 15 \) steps up to its maximum recall value and measure the number of correct responses retrieved at each step \( \lambda \).

According to [24] the micro-averaging of recall and precision (at the generic step \( \lambda \)), is defined as follows:

\[
\text{Rec}_\lambda \sum_{\Omega} \left| \frac{R_{\Omega} \cap B_{\lambda,\Omega}}{R} \right| \quad \text{Pr e c}_\lambda \sum_{\Omega} \left| \frac{R_{\Omega} \cap B_{\lambda,\Omega}}{B_{\lambda}} \right|
\]

where \( R_{\Omega} \) is the set of correct responses for a given situation \( Q_i \), \( B_{\lambda} \) the set of returned responses at the step \( \lambda \) and \( B_{\lambda,\Omega} \) is the set of all correct responses, retrieved at the step \( \lambda \), for the query \( Q_i \).

Figure 3 shows the tendency of the micro-average of recall/precision curve evaluated on the collection set, comparing our approach with SBSR.

Let us note that with values of recall lower than 0.6, the precision is higher than the curve SBSR of 20%, while with value of recall greater then 0.6, the two curve are quite similar, although the curve becomes 1 for SBFR.

This improvement is mainly due to the hybrid approach that combines fuzzy logic and description logic. On the other hand, swarm intelligence allows us to perform distributed reasoning on situations.

II. CONCLUSIONS AND FUTURE WORKS

In this paper, we present a swarm-based approach to fuzzy reasoning to support situation awareness in several complex domains. In particular, this work emphasizes the swarm behavior that is essentially based on the evaluation of fuzzy controls and where the swarm infrastructure is represented by RDF graph of situations data model. Fuzzy control evaluation performs distributed reasoning on acquired data in order to forecast emerging situations. This work relies on the semantic annotation of heterogeneous sensors data according to Sensor Web infrastructure and the modeling of situations according to FSTO.

The main aim is related to define a framework in order to autonomously push out emerging situation by processing large and dynamic knowledge base. The preliminary experimental results highlight the goodness of this combined approach with respect to others that don’t explicitly manage uncertain knowledge. A future extension of this approach foresees automatic fuzzy control design [23]. In particular, a fuzzy reasoner to support relevant situation notification could be automatically trained according to historical data. Further works concerns with the refinement of fuzzy based swarm behavior and tests running in several scenarios.

REFERENCES


