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Unified Modeling of Quality of Context and Quality of Situation for Context-Aware Applications in the Internet of Things

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Abstract. This paper discusses the requirements of situation identification in the Internet of Things and the necessity to consider the quality of the input context data during the inference process for deriving a situation and evaluating its resulting quality. We propose to extend previous works by integrating the QoCIM meta-model within the muSIC framework dedicated to situation identification. Situation identification is derived using an ontological approach and Quality criteria are aggregated using the fuzzy Choquet operator for computing the quality of a situation. This paper shows that QoCIM allows to model quality of context (QoC) as well as quality of situation in a unified approach.

1 Introduction

Multiple and heterogeneous sources of information such as open data, social networks, clouds, wireless sensor networks, and the Internet of the Things are now able to provide context data and contribute to the development of new mobile and context-aware applications. However, context data are known to be inherently uncertain [7] and an evaluation of their quality is essential in order to take relevant decisions based on these context data. We distinguish context data from context information in that raw data are unprocessed and retrieved directly from a data source, such as a sensor, and context information is obtained by processing raw context data.

The IoT is characterized by the extreme heterogeneity and large quantity of objects it can interconnect, as well as the spontaneous nature of their interactions. To deal with the enormous amount of context data collected from the IoT, new solutions are thus necessary to add value to these context data and identify contextual situations of high level of abstraction relevant to the applications. This paper focuses on solutions for measuring the quality of the identified situation resulting from the analysis and agregation of multiple context data of diverse quality. Quality of context (QoC) must therefore be integrated during the whole processing chain from the acquisition of raw context data to the identification of high level context situation.

2 Related Works

Situation identification calls for reasoning techniques for deriving high level and meaningful information from raw context data. Moreover, one way to integrate quality in the reasoning process is to use methods to aggregate the various quality indicators attached as meta-data to context data, as can be done with QoCIM [9], into a unique indicator measuring the quality of the identified situation. We review below, firstly, some reasoning techniques and, secondly, aggregation techniques and discuss their relevancy to the case of the IoT where a high amount of data come from heterogenous and dynamic context sources.

[11] classifies context reasoning techniques into six broad categories, namely supervised learning, unsupervised learning, rules, fuzzy logic, ontological reasoning and probabilistic reasoning. This analysis shows that for the IoT, the most promising methods are fuzzy logic and ontological reasoning. Fuzzy logic enables approximate reasoning using confidence values representing degrees of membership to a given interval. Truth values may be defined in natural language allowing to deal with uncertainty. Ontological reasoning is based on description logic and is supported by semantic web languages such as RDF or OWL. Ontologies allow complex reasoning and can manipulate both numerical and textual data.

For aggregating multiple QoC criteria, constraints are given by the IoT. Weights may be attributed to QoC criteria but cannot be static and should be determined dynamically as runtime conditions change. Context data as well as QoC criteria are heterogeneous and cannot be restricted in type. Additionally, aggregation should consider QoC criteria of various types to be aggregated in a new criteria of potentially a different type. Therefore a generic solution is required to aggregate primitive criteria into a composite criterion deduced in an automatic manner. Classical linear combination operators are limited to static weights. Fuzzy operators such as OWA (Ordered Weighted Averaging) are more promising. OWA allows to select the criteria to be aggregated and cannot represent any interaction among criteria. The Choquet integral [4] can be seen as a generalization of OWA and can be used in cases [5] where dependencies exist among criteria as it gives a weight to each criterion as well as to the series of values of the alternative combining the remaining criteria.

3 Integrating QoC in the process of situation identification

We present in this section how we take into account QoC in the reasoning process for identifying situations. QoC is modeled using the QoCIM meta-model [9], and situation identification is performed by the muSIC framework.

3.1 QoCIM : A Meta-model for Managing Quality of Context

Context data are known to be inherently uncertain due to the imperfection of physical sensors and the difficulty to model the real world [1,7]. Therefore,

taking into account the knowledge of the quality of context (QoC) [3] becomes essential for the system to suggest relevant decisions to applications. Several works have proposed their own vision of QoC with a list of criteria. We have proposed the Quality of Context Information Model (QoCIM) [9] in an effort to leverage previous works addressing QoC in order to represent any QoC criterion and indicator. It results from an analysis of context-aware management systems proposed over the last 15 years [8] as well as the QoC criteria proposed in the literature. This study enabled us to identify relevant design elements and the required properties of the solution: (1) Expressivity to manipulate context information according to its QoC level. (2) Genericity to ensure interoperability of QoC metadata exchanged among all the entities of the context manager. (3) Calculability to allow information sources to evaluate the quality of the context information they produce and consumer entities to interpret or transform the QoC values they receive. QoCIM¹ allows to manipulate any type of QoC criterion during context lifecycle and comes with a tool suite for generating Java source code for manipulating QoC and a library of computing functions such as aggregation, inference, filtering, etc. [10].

3.2 muSIC : Detecting situations of interest

With the increasing amount of context data available in the IoT, detecting situations of interest in pervasive systems is a crucial feature. This helps such systems to focus on meaningful situations in which relevant actions should be performed. In the INCOME project, we combined an Ontological Context Manager (OCM) with an Adaptive Multi-Agent System (AMAS) for providing the muSIC (multi-scale Situation Identification from Context) framework for an adaptive solution for situation identification [6]. The OCM module enables to represent a situation with an ontology and a set of static rules. It receives raw context data and derives context information of a higher abstraction level. The AMAS module then analyses these abstracted context data relying on agents that consider rules provided by OCM in order to identify situation types at runtime.

We define a situation as "a set of semantic relations between concepts (in one context dimension or between several context dimensions) which are valid and stable during an interval of time", where the term dimension means a context type such as location, time, activity, etc. [2]. This definition distinguishes context and situation. In a situation, meanings are assigned to context data, a set of sensor data may be considered as a context dimension, and temporal aspects are involved. A *situation* is represented by all the numerical or semantical values of the characteristics of a set of information. A *situation type* is a semantic value (modelled as a string) that can be associated with several situations. A situation type is defined by a set of conditions. Each condition relates to the possible values of a characteristic of a data (but a situation type does not have necessarily a condition for every characteristic). For example, the situation type "AtWork" is

¹ <https://fusionforge.int-evry.fr/www/qocim/>

associated with the situations : "I am at Lab on monday at 8:05 AM", "I am at Lab on monday at 9:38 AM", etc.

3.3 Contribution

Figure 1 illustrates the integration of muSIC and QoCIM within a Distributed Context Manager. MuDEBS² and muContext³ constitute the core of the Distributed Context Manager developed in the INCOME project. Based on these frameworks, QoCIM is able to qualify both context data acquired from context producers and high level context information delivered to end-user applications through meta-data.

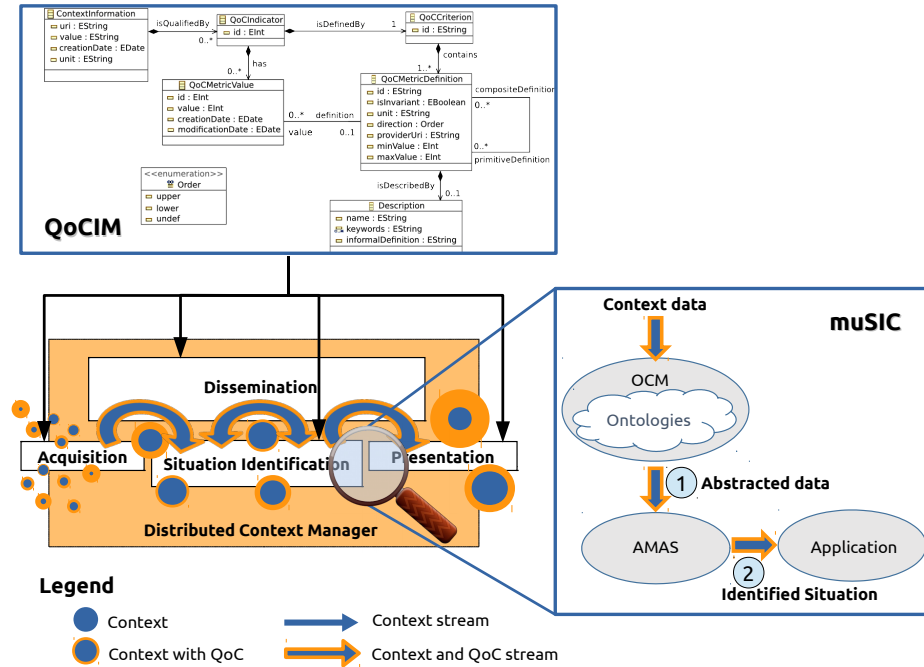


Fig. 1. QoCIM integration with muSIC

MuSIC is deployed within software entities that consume and produce qualified context information. The purpose of these entities is to identify qualified situations based on context data as described in Section 3.2. The qualified situations are then used by end-user applications to offer more advanced services and suggest different recommendations. To identify high level situations, the muSIC

² <https://fusionforge.int-evry.fr/www/mudebs/>

³ <https://fusionforge.int-evry.fr/www/mucontext/>

process is divided into two steps. OCM first extracts abstracted data from qualified context information coming from the acquisition layer of the Distributed Context Manager. An AMAS then derives qualified high level situations for end-users applications. The situations are finally delivered in the presentation layer of the Distributed Context Manager.

The abstraction level of the criteria used to qualify context data and situations follows the abstraction level of the information. As a consequence, low level criteria, “precision”, “accuracy”, “freshness” for example, are associated to context data while high level criteria, for example “trustworthiness”, are used to qualify identified situations. As discussed in section 2, a Choquet fuzzy operator is relevant for aggregating multiple quality criteria of different types and has been implemented. In our solution, all of these criteria are modelled and manipulated using the computing operators provided by the QoCIM framework.

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