User-driven Design of Ontology-based, Context-aware and Self-learning Continuous Care Applications

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***Abstract*—A plethora of technologies is adopted in modern continuous care settings. Nowadays, the nurse is responsible for orchestrating all these devices to take advantage of the collected information. This causes caregivers to lose time, miss out on patient insights and lack a general overview of the situation. In this paper, an ontology-based and self-learning context-aware platform is presented. This platform combines pervasive and context-aware techniques with knowledge management techniques to leverage the aforementioned problems and allows to easily build intelligent applications to support caregivers in their everyday activities. Moreover, a self-learning framework is proposed, which allows detecting trends in the usage of these applications and adapting them accordingly. However, the integration of context-aware technologies can prove to be difficult if domain experts are not involved in the development process. This increases the fear of the technology, makes the staff feel less in control and empowered and causes that the technologies are not tuned towards the work processes of the staff. Therefore, a participatory ontology engineering methodology is also presented which allows involving the stakeholders in each part of the development process of context-aware applications.**

I. Introduction

In recent years the complexity in nursing organizations has increased due to societal factors, e.g., the increase of the care unit size and specialized care and the lack of nurse staffing which requires a more efficient use of resources. A further increase of complexity is due to the high amount of new technologies that are being adopted, especially to support administrative tasks, data management and patient monitoring. The challenge today is that several devices have to be manually combined and consulted by the staff to take advantage of the information collected by all this technological equipment, even when carrying out one single task [1]. Due to the fact that the available data is not being integrated and aggregated, caregivers lose time, miss out on potential patient insights and lack a general overview of the situation.

To cope with these problems, ambient-intelligent, pervasive and context-aware techniques are often introduced. The common denominator of these techniques is that the technology will blend into the background of the environment and sensors and actuators will be able to sense and adapt our environment [2]. This implies an emerging demand for the integration and exploitation of the heterogeneous information available from all the devices such that the caregivers no longer play the role of the orchestrator between all these technologies. Moreover, this information integration allows building intelligent applications which exploit all this available data to support the caregivers in their everyday activities.

To mediate the aforementioned problems, this paper presents an ontology-based context-aware platform, which allows easily developing pervasive applications. To easily build intelligent applications, the platform must be able to interpret the meaning and adequately filter the relevant information out of the huge amount of heterogeneous care data provided by the all the devices and sensors. Unorganized data is voluminous, but has no meaning on itself as it has no relationships or context. To transform the data to information, which is data that has been given meaning by defining relational connections, the platform employs ontologies [3]. An ontology is a semantic model that formally describes the concepts in a certain domain, their relationships and attributes. In this way, an ontology encourages re-use and integration. By managing the data about the current context in an ontology, intelligent algorithms can be defined that take advantage of this information to automate, optimize and personalize the continuous care of patients. Ontologies thus effectively separate the domain knowledge, which can be re-used across different applications, from the application logic, which can be written as rules on top of the ontology.

However, the introduction of context awareness into commercial products is lagging behind what could be expected. This is due to inadequate techniques for personalization of the services, a lack of focus on the soft aspects of interaction, e.g., automated and personalized alerts, and the lack of tackling problems such as the fear for technology and the need of the users for control [4]. To ensure that technology and environment melt into each other, the users should be involved in each step of the development cycle of context-aware applications. To achieve such a user-centered development process, this paper presents a participatory ontology engineering methodology, which involves the users in each step of the ontology life-cycle.

Finally, to make the developed context-aware applications more adaptable to future needs, this paper proposes a self-learning framework which allows detecting trends in the usage of these applications and adapting them accordingly.

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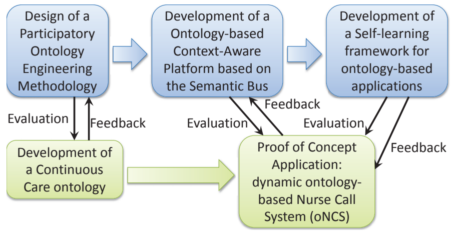

Fig. 1. Workflow of the iterative methodological research approach.

The remainder of this paper is organized as follows. Section II details the research questions addressed in this paper. Section III discusses the methodological approach used to conduct the research and describes the work done to date. Finally, Section IV highlights the future work and remaining open questions.

II. Main Research Objectives

To address the problems discussed in Section I, this research focuses on the following research questions:
- How can the heterogeneous continuous care data gathered from the sensors & devices and communicated between the applications be modeled in a formal and semantic manner?
- How can intelligent algorithms & applications to optimize continuous care be built based on the developed model?
- How can these context-aware applications be developed in a user-driven manner to increase acceptance of the new technology and empower the staff members to take control of this technology and adapt it to their needs and daily activities?
- How can the large amount of heterogeneous data be dynamically filtered such that the different applications only receive the data that is relevant to them at that moment?
- How can the model and accompanying algorithms be made adaptable to future needs in a constantly changing world?

III. Methodology

Figure 1 shows the iterative methodological approach used in this research. The components are detailed in the following subsections.

A. *Participatory ontology engineering methodology*

In the developed context-aware platform, see Section III-C, ontologies are used to model the heterogeneous continuous care data gathered by the different sensors & devices. This allows building intelligent applications that use this integrated knowledge.

The existing ontology engineering methodologies are rather extreme in their choices to include domain experts. There are methodologies [5], e.g., Tove and Methontology, that only discuss the scope and requirements of the ontology with the domain experts. Recently, a human-centered approach (HCOME) [6] was proposed, which offers user-friendly tools to domain experts to construct, merge and discuss their own ontologies. The knowledge engineer only delivers technical support. To achieve a middle ground between these two extremes, a participatory ontology engineering methodology was developed and evaluated in this research [7]. The methodology actively involves social scientists, ontology engineers and stakeholders. It promotes user participation while taking into account that time is a valuable resource within the eHealth domain.

The methodology starts by composing a representative stakeholder group and organizing a hands-on workshop to explain to them what ontology means and what ontology engineering entails. Next, the ontology engineers and social scientists perform observations in representative settings about current daily practices and analyze logging data from the available systems. This first stage ends by defining the scope and requirements of the ontology by constructing a sunny day scenario, detailing the hypothetical use of the context-aware system by representative user archetypes in which the technology is unconstrained by current technological possibilities.

In the second stage a conceptual model is created by organizing role-playing workshops based on the sunny-day scenario. During these workshops the engineers build a graph visualization of the concepts and their relations identified during the role-play and the ensuing discussions. This graph is iteratively discussed with the participants. The resulting ontology is mapped on existing ones to identify ontologies that can be reused. Finally, the graph model is fleshed out with concepts identified during the observations.

In the third stage the conceptual model is transformed into a formal one by defining axioms that restrict the possible interpretations of the concepts by first extracting these axioms and rules from the observations. To fill in the remaining formal gaps, decision-tree workshops are organized in which the stakeholders are enticed to discuss the decision process they find ideal to solve a particular problem, e.g., assigning care requests. Simultaneously, the ontology engineers formalize this decision process in a decision tree in which the nodes represent the concepts on which the decision is based.

In the fourth stage, engineers implement the formal model in a knowledge representation language. Stakeholders are not actively involved in this stage to not overburden them. However, to prevent losing sight of the user requirements, the ontology is constantly validated with the sunny-day scenario.

Finally, in the maintenance stage, the ontology is continuously evaluated and updated to reflect changes in the domain. Additional role-playing workshops are organized and Proof-of-Concept (PoC) applications are made using the ontology to discuss and demonstrate its possibilities.

B. *Continuous care ontology*

The participatory ontology engineering methodology was evaluated by constructing an ontology for the continuous care domain. The evaluation is thoroughly discussed in Bleumers, et al. [8]. The creation of this ontology allowed to iteratively fine-tune the methodology. The stakeholder group consisted of staff of two institutionalized continuous care settings, namely a residential care setting and a hospital, caregivers from other institutions and professionals working for the healthcare industry, e.g., a nurse call system company. Observations were performed in the two settings and the various workshops were performed multiple times with different representatives of the stakeholder group. As PoC an ontology-based nurse call system was built, as discussed in Section III-D and described in Ongenae, et al. [9].

The difference between residential care and hospitals is that the first focus more on care, while the latter focus more on curing the patients. Consequently, the ontology was split into a high-level ontology, modeling the concepts used with the same meaning within both settings, and two low-level ontologies, one focusing on care and the other on cure. The high-level ontology consists of 7 parts [7]: the upper ontology (importing the SWRL Temporal Ontology[1]), the sensor ontology (based on the WSN Ontology [10]), the role & competence ontology, the context ontology, the profile ontology, the task ontology (importing the OWL-S Process Ontology[2]) and the medical ontology (importing the Galen Ontology[3]).

C. *Ontology-based context-aware platform*

The ambient-intelligent nursing organizations of the future consists of various devices and sensors that generate huge amounts of data and intelligent applications that process this data. A Semantic Communication Bus (SCB)) [11] was developed to process the data and forward it to applications that are interested in it. The SCB uses ontologies to interpret the data being communicated. The devices and sensors publish data on the SCB that adheres to concepts in the ontologies. Applications, which use a subset of the ontologies of the SCB, can define the information they are interested in by specifying filter rules. These rules are expressed using concepts from the ontologies. Consequently, when continuous care information is published on the SCB, it is matched with the filter rules and if a match is found, the data is forwarded to the applications that registered these rules. The applications process the received data and as a result adapt the environment by controlling the devices or publish their conclusions back on the SCB to be used by other applications. The use of these filter rules reduces the amount of care data that is forwarded to the applications.

D. *oNCS system*

An important way to coordinate work, communicate and provide continuous care is a nurse call system [12]. Traditional systems, as shown in Figure 2a, are static as calls are made by buttons fixed to a wall and the nurse call algorithm consists of predefined links between rooms and caregivers. The system thus does not take into account the factors specific to a situation, e.g., the patient's risk factors or the staff's locations.

To evaluate the context-aware platform presented in Section III-C, an ontology-based Nurse Call System (oNCS) was developed [13], as shown in Figure 2b. The oNCS allows patients to walk around freely with wireless call buttons. The profiles of the staff and patients are efficiently managed with the ontology discussed in Section III-B. A nurse call algorithm was designed that adapts to the specific situation by taking

[1]http://protege.cim3.net/cgi-bin/wiki.pl?SWRLTemporalOntology
[2]http://www.w3.org/Submission/OWL-S/
[3]http://www.opengalen.org/

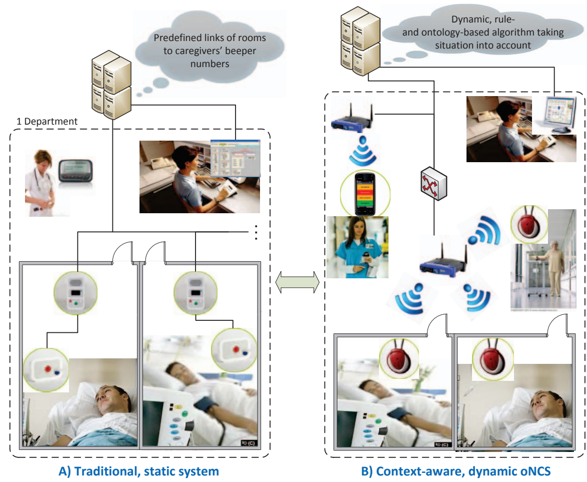

Fig. 2. Traditional, static call system vs. the context-aware, dynamic oNCS

the profile information into account, e.g., the location and characteristics of the staff and patients, the staff's current tasks and the priorities of the calls. This information is used to find the best caregiver to handle a call. To study the impact of this new algorithm simulations were run to compare the traditional system to the oNCS. Figure 3 shows the number of calls that have a nurse present as a function of the arrival times of these nurses. After 60 sec., most calls have a nurse present in the oNCS, while only half of the calls have a nurse present in the traditional system.

The users were involved in every step of the oNCS design process. First, they participated in developing the ontology on which the oNCS is based, as discussed in Section III-B. Moreover, the caregivers expressed their view on how they wished nurse calls would ideally be prioritized and assigned in decision-tree workshops. This allowed building a first mock-up of the oNCS, which was presented to the stakeholders in an instructional movie. Group discussions about specific functionalities of the mock-up were also held. This resulted in considerable feedback for the nurse call algorithm.

Finally, a completely functional PoC implementation of the oNCS was built. Subsequent workshops gave the participants a first-hand experience of the PoC in order to generate deeper reflection on both the application and the ontology. After an elaborate introduction, the participants were given persona and context cards and were asked to try out some of the functionalities by role-playing. In between and afterwards, the participants and the researchers discussed the application. These workshops resulted in feedback on the application, but no changes were made to the ontology. This could mean that the method was less suited for ontology feedback, but it can rather be understood as a confirmation of the ontology.

The scalability and performance of the oNCS was also evaluated. It is known that attention should be paid to the number of instances in the ontology as this adversely affects the reasoning performance [14]. Consequently, if all the data from the ambient-intelligent environment would be delivered directly to the oNCS, its performance would degrade drasti-

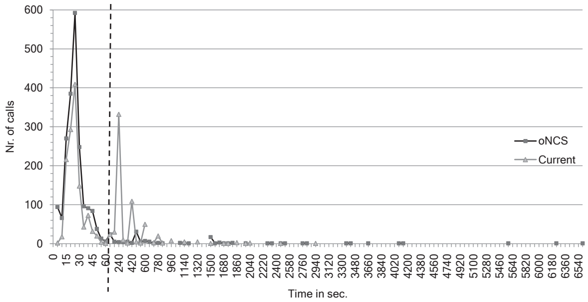

Fig. 3. Number of calls as a function of the nurse arrival times. The time-step is 5 sec., in the first of the x-axis and 60 sec. in the second part.

cally. By using the SCB, filter rules were defined such that the oNCS only receives relevant context data. When a call is launched, the oNCS notifies a suitable nurse within 50.33 ms on average, which is a negligible delay [13].

E. Self-learning framework

When new technology is introduced, the behavior of the users changes to adapt to it. This means that the ontology might be incomplete or the algorithms of the applications built on it may no longer apply. However, it is difficult to predict which additional knowledge will be used. To make the context-aware platform adaptable to future needs, research on a self-learning component is on-going. A first architecture is shown in Figure 4.

First, *Indicator Algorithms* determine missing knowledge in the ontology. An example: situations are logged where a suggestion is given by the system to the staff to do an action, but the caregivers consequently do a different action under certain circumstances. The results of the *Indicator Algorithms* are shown to *domain experts & application developers*. As a result a learning step can be initiated. The input and output parameters are specified in the *Configuration Module* and the *Data Collection Module* automatically extracts the appropriate data from the ontology. The *Pre-Processor* contains several modules to clean up the data, e.g., remove outliers, scale the data, interpolate or perform feature extraction. The cleaned data is then passed to the *ML Component* that provides several Machine Learning (ML) techniques, which can be used on the data to discover trends, e.g., Clustering, Classifiers and Bayesian networks. The conclusions of the *ML component* are studied further by *Filter Algorithms*. These algorithms filter out of these conclusions the knowledge that should be added to the ontology and the new Rules that should be defined. For example, if the ML outputs the data organized in clusters, these algorithms analyze the similarities in the data in these clusters and define new Rules. Finally, the new knowledge can be integrated in the ontology and Rules with the *Integration Component*. The *Consistent Integration Algorithm* defines probabilistic relations that connect this new knowledge to the existing knowledge. This probability ensures that this new knowledge does not make the ontology inconsistent. Moreover, it makes clear to the stakeholders that this new knowledge has not been confirmed by rigorous evaluation.

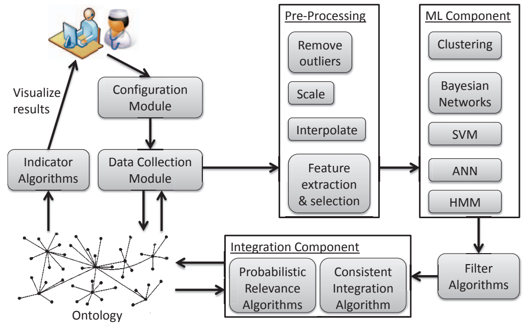

Fig. 4. Architecture of the self-learning component.

The domain experts can assign this initial probability. However, *Probabilistic Relevance Algorithms* are also provided which automatically determine the initial probability of this knowledge. Additionally, these algorithms in- or decrease the probability depending on the new information that comes available about usage of this knowledge.

The *Pre-Processor*, *ML Component* and algorithms to add and reason on probabilistic data in the ontology were already researched and evaluated [15].

IV. FUTURE WORK AND REMAINING OPEN QUESTIONS

Future work will concentrate on two main parts. First, the maintenance step of the participatory ontology engineering methodology will be further developed. A PoC was developed to ensure cross-institutional validity of the ontology. The PoC workshops resulted in a lot of feedback on the PoC, but it was unclear to what extent this method was also successful for validating the ontology. Moreover, the PoC only covered some elements of the ontology. Given the high time investment needed for organizing the workshops and developing the PoC, it seems unrealistic to develop several PoCs in order to cover every element in the ontology. To further validate the ontology, we are looking into methods to automatically translate an ontology into a natural language description of its concepts. We are also looking for other methods to validate the large ontology together with the users.

Second, the self-learning component will be further developed and investigated using the oNCS system. A remaining research questions for the *Filter Algorithm* is whether all the detected trends should be added to the ontology. Wrong trends could be detected because of skewed or too small data sets. It also important to only include trends that reflect good and general work practices. Wrong information could clutter the ontology and make the application less useable. However, it is often difficult, even for domain experts, to validate the correctness of a detected trend. Finally, open questions also remain about the *Probabilistic Relevance Algorithm*. How should the initial probability be determined? Some ML techniques associate a probability with the trend, which could be used. Moreover, this probability should in- and decrease as new information comes available. It is however difficult to assess how fast this in- or decrease should happen and on which it should be dependent.

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