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Enhancing ontological reasoning with uncertainty handling for activity recognition

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ABSTRACT

Ontology-based activity recognition is gaining interest due to its expressiveness and comprehensive reasoning mechanism. An obstacle to its wider use is that the imperfect observations result in failure of recognizing activities. This paper proposes a novel reasoning algorithm for activity recognition in smart environments. The algorithm integrates OWL ontological reasoning mechanism with Dempster–Shafer theory of evidence to provide support for handling uncertainty in activity recognition. It quantifies uncertainty while aggregating contextual information and provides a degree of belief that facilitates more robust decision making in activity recognition. The presented approach has been implemented and evaluated on an internal and public datasets and compared with a data-driven approach that is using hidden Markov model. Results have shown that the proposed reasoning approach can accommodate uncertainties and subsequently infer the activities more accurately in comparison with existing ontology-based recognition and perform comparably well to the data-driven approach.

1. Introduction

Smart home is a promising solution for elderly people who are dependent and require assistance in their activity of daily living (ADL). It incorporates and integrates multimodal sensors, actuators, devices, information and communication technologies with the aim at providing automated and safe environment for elders and hence facilitating independent living at home [1,2]. One of the main components of the smart home is a distributed monitoring system for inferring activity, health status and potentially dangerous situations for the inhabitants. Consequently, the system will generate alarms and send alert messages for preventive measures. Activity recognition in an environment still faces a number of challenges. Firstly, the activities performed by persons depend on their habits and lifestyle and hence they are carried out in different sequences and with different durations. Although there exist correlations among some activities, there is no strict pattern in a sequence of activities. Secondly, multimodal sensors embedded in smart home environment generate heterogeneous data that varies in terms of formats, sensing rates and semantics. Furthermore, a fusion of these sensor data is required to establish the context of the activity being carried out. Finally, uncertainties are always present in ambient intelligence environment [3]. For instance, sensor data are inherently noisy. This can be due to sensor errors (run out of batteries, imprecise outputs, missing activations etc.), communication failures and variability in human activities. These issues may significantly influence the accuracy of activity recognition.

Different approaches have been proposed by researchers for activity modeling and recognition. They can be classified into data-driven and knowledge-driven approaches [4,5]. Data-driven approaches use learning-based techniques with robust activity models that extract specific features from sensor data. The main advantage of learning-based techniques is the ability to handle uncertainty and noise. Previous research works have shown that they are able to obtain high accuracy rate of activity recognition [6–14]. Furthermore, learning-based techniques are applicable to different domains and achieve good results [15,16]. However, data-driven approaches tend to suffer from the curse of dimensionality and require large amount of initial training data sets to train activity models. As users perform activities in various ways and orders, it is difficult to obtain sufficient and representative datasets [4,5,17]. Moreover, collecting and manually annotating huge amount of sensor data is an extremely time-consuming task. Therefore, data-driven approaches suffer from scalability, applicability and adaptability [5,18,19].

Knowledge-driven approaches exploit prior knowledge to build semantic activity model by using knowledge engineering techniques (also called specification-based techniques), and then rea-

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son on it with input sensor data. The advantages of these approaches are interoperability and ability of adaptation to different scenarios, which are essential for context-aware environment where the sensors are multimodal. Moreover, they provide a way to represent sensor data and contexts by a formal data structure with the aid of semantic descriptions, which makes them understandable to both human and machine. Consequently, they facilitate the development of semantic activity model and recognition process. Numerous knowledge-based techniques have been introduced for context modeling. The simplest forms of context modeling are key-value pairs and markup schemes such as Composite Capabilities/Preference Profile (CC/PP) [20] and more expressive forms such as object-role based models [21] and logic-based models [22]. Although these techniques offer benefits such as context abstractions and support for reasoning, ontology-based models have become preferred for managing and modeling context recently [5,23]. Ontology is a formal and explicit way of specifying and representing domain knowledge through formal axioms and constraints. Ontology-based models have several advantages over other models [19,23,24]. Firstly, they allow the domain knowledge to be decoupled from the operational knowledge. Next, they have strong support through standardization such as Resource Description Framework Schema (RDF) and Web Ontology Language (OWL) and hence a variety of development tools are available. Finally, rules which are tightly integrated into reasoning can be expressed via Semantic Web Rule Language (SWRL). Despite the advantages of ontology-based technique, there are still limitations that must be tackled: ontological reasoning is computationally expensive, support for modeling temporal information is minimal and they cannot deal with uncertainty.

In this paper, we are focusing on the weakness of ontology-based techniques to deal with uncertainty, because it affects the accuracy of activity recognition [3]. There are three levels of uncertainty in decision making process: data uncertainty, comprehension uncertainty and projection uncertainty [25]. Data uncertainty is normally associated with errors in sensor's measurements, which arises due to incompleteness (missing sensor data), imprecise, inaccurate, timeliness and incongruent [5,25,26]. This study is focusing on incompleteness which is the most common in smart home environments because sensors operate with certain degree of reliability or loss of data during transmission. Existing ontology-based activity recognition systems can only infer an activity when all the contextual information that defines the activity is asserted. The contextual information is captured by the sensors embedded in the environment. If one of the sensor data is missing, ontology will not be able to infer the activity that is being carried out, which is indicated by a total ignorance about the current situation in the environment. In Dempster–Shafer (DS) [27,28] theory, total ignorance can be assigned with a weightage (called belief) and combined with other evidences with a series of mathematical functions. Furthermore, DS theory can also resolve conflicting data by combining the evidences and arriving at a degree of belief [5,29] to facilitate the activity recognition process.

In this paper, we propose a novel reasoning algorithm which integrates ontological reasoning based on Description Logic (DL) [30] with DS theory. The proposed algorithm maintains the advantages of ontological reasoning and has the ability to manage data uncertainties that occur during the activity recognition process. An activity is modeled as a sequence of actions separated by elapsed time between two actions and may be used to represent the real-life activity. The reasoning algorithm assigns degree of beliefs to actions based on their states: active, inactive or uncertain which are determined by using the actions' temporal sequence and inference of the actions. Then, the algorithm aggregates the action contexts to produce a belief for the activity which supports the decision making of activity recognition process. In addition, we propose a four-layered activity ontology which systematically organizes the contextual information in accordance with the activity inference process. We also propose a methodology to incorporate the evidential parameters in the ontology for reasoning using DS theory. The new algorithm is applied on two datasets, one collected internally and one publicly available, and then compared with ontology-only based recognition approach and data-driven approach. It shows very good recognition accuracy compared with other approaches.

The rest of the paper is organized as follows. The related works on activity ontologies and reasoning approaches to handle uncertainty and their limitations are presented in Section 2. The mathematical model of ontological reasoning under uncertainty and the evidential operations are presented in Section 3. Activity ontology and the representation of evidential parameters are described in Section 4. The proposed reasoning algorithm that manages uncertainties to support activity recognition is described in Section 5. The results of algorithm performance, as well as the comparison with the data-driven approach, are presented in Section 6. Finally, conclusions and future work are presented in Section 7.

2. Related works

2.1. Ontologies for activity recognition

A number of ontology-based systems have been developed for activity recognition. In [31], an DL-based reasoning engine is used to recognize coarse-grained and fine-grained activities. Bae [32] proposed a method for recognition of activities of daily living. Ontology is used to model the activity while semantic reasoning and rule engines are used to recognize the activities. Okeyo et al. [33] proposed a novel sensor data segmentation approach for activity recognition. Activities are modeled using ontology and semantic reasoner is used to recognize the activities. Ye et al. [34] present a novel ontology-based approach for concurrent activity recognition. Semantic dissimilarity is used to segment a continuous sensor sequence into fragments, which corresponds to one ongoing activity. In [35], an ontology-based hybrid framework for activity recognition is proposed by combining the standard reasoning semantics of OWL 2 and the standard query language of the Semantic Web. The proposed framework allows the OWL 2 reasoning module to incorporate temporal correlations of complex activities which is essential in activity recognition. Khattak et al. [36] proposed an approach to improve the general health and life status of elderly peoples by monitoring the dietary intake and health activity information. The ontology is used to model the daily life activities and patient profile information, allowing the analysis of fine-grained situation for personalized service recommendations. Ahmadi-Karvigh et al. [37] proposed a novel ontology-based framework to allocate appliance-level electricity consumption to daily activities. In the framework, appliance usage data is separated into categories of activity events, which are next segmented into activity segments. Then, a classification model is used to classify the activity segments into activity classes. None of the aforementioned approaches address uncertainty in activity recognition scenarios. Riboni and Bettini [38] proposed a hybrid reasoning for activity recognition which combines data-driven and knowledge-driven approaches called COSAR. In COSAR, statistical classifier recognizes an activity which is then tested through consistency checking by ontological reasoning to verify the recognition. COSAR can deal with uncertainties since machine learning technique is used as the classifier. However, the approach suffers from data scarcity to train the activity model. In [39], a novel unsupervised approach that combines data-driven and knowledge techniques for mining activity recognition is proposed. The ontology is used to represent the domain knowledge for facilitating the unsupervised discovery of ac-