Towards a Proactive System Based on Activity Recognition

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I. Introduction

Recent progress in sensing technology has led to ever more inexpensive and smaller sensors. This has opened the door for novel applications. A particularly promising one is what is called "proactive computing" [1], which suggests an anticipatory aspect to ubiquitous computing. An anticipatory system can be defined as "a system containing a predictive model of itself and/or of its environment that allows it to change state at an instant in accord with the model's predictions pertaining to a later instant" [2]. In order to generate and maintain such predictive models, a system needs context-awareness, that is, the ability to determine what to observe in its environment and how to interpret it [3]. The predictive models allow the system to pro-actively adjust to changes in the real-world. In this work, we address underlying principles of preventive systems for proactive applications in closed domains.

II. Problem Statement

One of the ambient healthcare objectives is to provide the growing population of elderly people and patients with special diseases with the needed help in time and at their own residence. While some emergency situations can be handled with purely reactive systems, for others, it might be necessary to anticipate their occurrence. An example would be a long term disturbance in the subject's daily rhythm indicating upcoming depressive state. Several recent works proposed to react to deviances using simple sensing like detecting significant changes in the subject's weight or blood pressure and then to trigger alarming reactions in case of serious anomalies [4]. This work, however, poorly addresses context-awareness which is mandatory for health monitoring and proactive services [5]. One of the ways to approach context are the so-called 5 Ws, namely: the "Who, Where, When, What, and Why". This immediately raises the following questions: which of these aspects are necessary to achieve the desired reactive and proactive aspects of our system? How to introduce and combine them to infer the current high level activity? Once the current state recognized, a proactive system needs to reason about next expected world states using its predictive model. Such a model includes a mapping from low level sensor data to high level symbolic states and activities. This evokes another aspect of the problem, i.e. which methods and learning paradigms are most appropriate to build the required model? Since human daily activities are usually of a non-sequential nature, they can often be interleaved or interrupted. Such activities, as well as activities engaging multiple subjects, represent a challenge. This leads to the question of how to detect and incorporate temporal qualitative and quantitative aspects of the activities in the aspired model? To summarize, our work is concerned with achieving a proactive framework based on accurate activity recognition and prediction using embedded real-world light-weight sensor data.

III. Related work

Recently, different ways to approach reactive and proactive services and activity recognition for Ambient Assisted living have been proposed. They can be classified according to many dimensions such as: (1) the learning paradigms, (2) the relevance of temporal information in the recognition model, and (3) whether the model is linked to real sensor data or simulated data. One step towards incorporating spatio-temporal context and uncertainty reasoning based on a belief rule-based system RIMER is described in [6]. They use active databases and their Condition-Action rules as a way to react to the incoming information. The decisions are taken at the detection of situations of interest defined by events occurring in particular contexts. The system, however, relies on a rule base generated by experts. Other knowledge-driven attempts proposed to minimize the uncertainties about user's intention recognition through creating an ontology and building a hierarchy and relationship among these intentions. Most of the current approaches to our problem are, nonetheless, data-driven. However, they seldom integrate temporal constraints in their systems as we intend to. The majority use supervised learning methods like Hidden Markov Models. Since obtaining substantial amounts of labelled data is often a bottle-neck for these approaches [7], recent efforts to explore unsupervised learning methods have arisen. In [8], web mining is used to automatically extract probabilities of the co-occurrence of some activities and the possibly used objects. These probabilities assemble a HMM capable of recognizing activities in traces of object data. Increasing interest can be noticed concerning weakly supervised learning like multi-instance learning [7] and semi-supervised learning methods. We conjecture that combining both paradigms, i.e. data-driven and knowledge-based, is an appealing direction to solve such non-Markovian problems. Similar to [9], our work also suggests to use both probabilistic models and relational information to transform the raw sensor

Advisors: Professor Dr. Stuckenschmidt and Dr. Niepert data into higher-level descriptions of people's behaviours and activities. In [9] all of the ontology based methods, web mining and HMM are used to produce a richly structured dataset describing people's daily patterns of activities. Due to the limited HMM temporal dependencies, however, we opt for Markov Logic Networks, which have been applied for activity recognition in [10] and [11]. Nonetheless, both works rely on video data. The use of such tracking systems implies some privacy and costs issues which we would like to avoid. Compared to [10], this raises new challenges like activity recognition of different actors. Indeed, distinguishing multiple subjects and their attributed activities demands more effort in absence of such video data. We also aim at an expanded set of more complex daily activities, addressing concurrent ones, as well as a richer temporal context. As proposed in [11], missing sensory data is an interesting aspect to be handled. Another similarity to our work is exploiting common-sense knowledge for a better model. The authors, however, limit their work to simple activities with no explicit consideration of the temporal context. Hence, existing approaches often rely on manually constructed sets of rules for recognizing activities. They rarely take temporal knowledge into account. This makes successful recognition of interrupted activities and activities engaging multiple actors rather out of reach.

IV. Expected contributions

Our main contribution is a framework towards proactive ambient healthcare systems. The approach relies on lightweight sensor data with real-world deployment. We expect our system to realise an active high-level-activities database with proactive services. It offers a good opportunity to:

- Reason with variably long user's behavioral history and explore the effect of different temporal contexts on the system's recognition and prediction accuracy.
- Allow for short and long-term prediction as well as intention recognition
- Extend the framework to the case of more than one actor.
- Investigate the viability of the system under limited availability of sensor data
- Apply it for the example case of anticipation and prevention of certain behavioral-symptoms-based diseases such as depression.

V. Approach

Our system consists of two modules: a reactive and a proactive one. In the reactive module, a particular rule simply triggers a reactive action if the current environment condition corresponds to an undesired state. In the proactive module, our system first generates the aspired predictive model based on a statistical relational approach. This choice is motivated by the rich set of common sense rules and constraints categorizing such activity based applications. The system periodically detects "events" from the ubiquitous sensors and learns non-temporal as well as temporal qualitative and quantitative rules. These rules and their confidences are combined with other mined "hard constraints" to build the predictive model. Once

```
sensor(table_plate,t),sensor(table_plate,t-1),
act("Clear The Table",t-1) ==> act("Clear The Table",t)(1.0)
sensor(espresso_switches,t) ==> act("Make A Vanilla Latte",t)(1.0)
sensor(cupboard,t),act("Make Tea",t-1) ==> act("Make Tea",t)(0.9)
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Fig. 1. Examples of ruled mined from the training data and their confidence. *The mined rules serve as initial rules and weights to train our MLN. Two predicates are used: sensor and act. The variable t stands for the current time step*

the current activity is recognized, the next expected state of the world is determined, that is the expected low level sensors data of the next time steps as well as the corresponding high-level activity. The prediction error of this input data can, then, be considered as an indirect feedback about the high-level activity prediction to improve the activities model's accuracy. It is also a good indicator for which sensor subset is relevant for the future time steps. Based on the recognized current state, the system can reason and predict a sequence of states or activities. If the predicted activity in a future time corresponds to one of the undesired states defined in the reactive module, the system anticipates the consequences and acts proactively. At a first stage, we start by using the data in [12] for recognition and prediction purposes. The dataset is mined and time-based rules are extracted along with corresponding confidence values. Examples of such formula are provided in Figure 1. Considering sensor data as "observation" and the current activity as "hidden" in our MLN, the system reasons based on the current state as well as the previous ones. At a further stage, we resort to the rich dataset of Ambient Assisted Living environment at Fraunhofer IESE[1] to implement and test the viability of the proposed framework.

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