An Event Calculus agent mind applied to diabetes monitoring

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Abstract. The increasing incidence of chronic diseases is a major challenge for the healthcare sector. Personal Health Systems (PHSs) address the self-management of chronic diseases, by decentralizing the health monitoring outside hospitalized environments. Rule based agents allow bringing domain experts' knowledge into PHSs. However, agents must meet the requirements of real monitoring scenarios, characterized by high streams of events. Hence, in this work, an agent mind for an agent-oriented PHS is presented. It is based on the integration of a Cached Event Calculus reasoner, jREC, with the aim to monitor the health status of diabetic patients. The paper analyzes the performance of the proposed agent mind, by computing the time needed to trigger different type of alerts, when the number of recorded events (e.g. values of physiological parameters) increases. The results show the usefulness of the agent mind in monitoring scenarios as well as clear room for improvement when many events (> 500) need to be checked.

1 Introduction

The incidence of chronic diseases in the population is recognized as a major challenge for the healthcare sector [2]. For instance, the number of people affected by diabetes has doubled in the last 20 years [29]. Statistics from WHO report that more than 400 million individuals live with diabetes, and losses in the GDP for diabetes-related costs from 2011 to 2030 are estimated at 1.7 trillion USD [28].

Personal Health Systems (PHSs) aim at supporting the self-management of chronic diseases and reducing the healthcare costs. They implement the "*healthcare to anyone, anytime, and anywhere*" paradigm, by increasing both the coverage and the quality of healthcare [27]. In fact, PHSs bring the health technology

to domestic environments, by localizing healthcare services to the specific needs, practices, and situations of people and their social contexts [20]. PHSs ensure the continuity of care, focusing on a knowledge-based approach integrating past and current data of each patient together with statistical evidence [25]. A PHS is composed of three tiers [26]: Tier 1 is the Body Area Network (BAN), i.e. the set of sensors on the patient's body to monitor her health parameters; Tier 2 is the personal server, usually a mobile device, which collects and aggregates the parameters and events produced by the BAN; Tier 3 is the remote server which processes and stores the data from the personal server and supports doctors in following the treatment of patients at home.

Beyond the modeling capabilities of agent-based frameworks [24], Multi-Agent Systems have been proved useful in the healthcare sector implementing modularity, distribution, and personalization for data management, decision support systems, planning and resource allocation, and remote care [14], being ideal for PHSs. In [7], an agent-based platform called MAGPIE implements a programmable expert PHS to monitor patients suffering from diabetes. In particular, that agent platform adds scalability to the PHS by shifting from Tier-3 to Tier-2 the computation needed for the patient monitoring. To obtain such scalability, the agents, composed by an agent body and an agent mind, run directly on the personal server. The agent body is the part of the agent that collects the data acting as an interface between the BAN in Tier-1 and the agent mind. The agent mind, based on an Event Calculus (EC) engine, is the part of the agent that checks the data collected from the body to perform the monitoring task and trigger alerts for the medical doctors logging in Tier-3. The approach of MAGPIE allows improving the scalability of the PHS when the number of patients increases, compared to a centralized PHS where the computation is performed in Tier-3. However, another aspect has to be taken into account: the scalability of the agent mind when the number of events increases. In fact, the use of rule engines based on EC usually restricts the number of events and rules to be applied in a real monitoring scenario, where short time delays are needed to apply corrective actions. Thus, the next step to apply the agent-based PHS in real scenarios requiring long-term monitoring is to develop agent minds capable of caching and retrieving events efficiently.

This paper addresses such issue by proposing an agent mind for the MAGPIE agent platform presented in [7]. The agent mind has been implemented using jREC, a Cached Event Calculus (CEC) reasoner based on Java and tuProlog [4], to move the computational complexity from query to update time by caching the maximum validity intervals for fluents. As the main contribution of the paper, the performances of the jREC-based agent mind are evaluated on the time required to trigger an alert, when the number of events generated by the agent body increases. Diabetes has been adopted as the use case for the monitoring rules to be checked.

The rest of the paper is organized as follows. Section 2 presents the paper background on EC, CEC, and jREC. Section 3 describes an overview of the entire PHS in which the agent mind runs, and shows the enconding of the moni-

toring rules to check alerts based on glucose and blood pressure levels in diabetic patients. Section 4 presents the experimental results to evaluate the jREC agent mind. Section 5 describes the work related to the presented research. Section 6 draws the conclusions of the paper and outlines the future work.

2   Background

This section introduces the concepts on which the proposed agent mind are based on.

2.1   Event Calculus

EC is a logic formalism for reasoning about actions and their effects in time [16]. Therefore, it is a suitable tool for modeling expert systems representing the evolution in time of an entity by means of the production of events. EC is based on many-sorted first-order predicate calculus, known as domain-independent axioms, which are represented as normal logic programs that are executable in Prolog. The underlying time model of EC is linear. EC manipulates fluents, where a fluent represents a property that can have different values over time. The term F=V denotes that a fluent F has value V as a consequence of an action that took place at some earlier time-point and not terminated by another action in the meantime. Table 1 summarizes the main EC predicates. Predicates, functions, symbols and constants start with lowercase letter, while variables start with uppercase letter. Predicates in the text are referenced as predicate/N, where predicate is the name of the predicate and N its arity (e.g. number of arguments).

The domain independent axioms of EC are the following:

$$\text{holdsAt}(F = V, 0) \leftarrow \text{initially}(F = V). \tag{1}$$

$$
\begin{aligned}
\text{holdsAt}(F = V, T) \leftarrow \\
\text{initiatesAt}(F = V, T_s), T_s < T, \\
\text{not broken}(F = V, [T_s, T]).
\end{aligned}
\tag{2}
$$

Predicate (1) states that a fluent F holds value V at time 0, if it has been initially set to this value. For any other time $T > 0$, the predicate (2) states that the fluent holds at time T if it has been initiated to value V at some earlier time point Ts, and it has not been broken on the meanwhile.

$$
\begin{aligned}
\text{broken}(F = V, [Tmin, Tmax]) \leftarrow \\
\text{terminatesAt}(F = V, T), Tmin < T, Tmax > T.
\end{aligned}
\tag{3}
$$

$$
\begin{aligned}
\text{broken}(F = V_1, [Tmin, Tmax]) \leftarrow \\
\text{initiatesAt}(F = V_2, T_i), V_1 \neq V_2, \\
Tmin < Ti, Tmax > Ti.
\end{aligned}
\tag{4}
$$

Table 1: Main Event Calculus predicates

Predicate	Meaning
initially(F=V)	The value of fluent F is V at time 0
holdsAt(F=V,T)	The value of fluent F is V at time T
holdsFor(F=V,[T_{min},T_{max}])	The value of fluent F is V between T_{min} and T_{max}
initiatesAt(F=V,T)	At time T the fluent F is initiated to have value V
terminatesAt(F=V,T)	At time T the fluent F is terminated from having value V
broken(F=V,[T_{min},T_{max}])	The value of fluent F is either terminated at T_{max}, or initiated to a different value than V between T_{min} and T_{max}
happensAt(E,T)	An event E takes place at time T updating the state of the fluents

Predicates (3) and (4) specify the conditions that break a fluent. Predicate (3) states that a fluent is broken between two time points Tmin and Tmax if within this interval it has been terminated to have value V. Alternatively, predicate (4) states that a fluent is broken within a time interval if it has been initiated to hold a different value.

$$
\begin{aligned}
\text{holdsFor}(F = V, [Tmin, Tmax]) \leftarrow \\
\text{initiatesAt}(F = V, Tmin), \\
\text{terminiatesAt}(F = V, Tmax), \\
\text{not broken}(F = V, [Tmin, Tmax]).
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
\text{holdsFor}(F = V, [Tmin, infPlus]) \leftarrow \\
\text{initiatesAt}(F = V, Tmin), \\
\text{not broken}(F = V, [Tmin, +\infty]).
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
\text{holdsFor}(F = V, [infMin, Tmax]) \leftarrow \\
\text{terminatesAt}(F = V, Tmax), \\
\text{not broken}(F = V, [-\infty, Tmax]).
\end{aligned}
\tag{7}
$$

Predicates (5), (6) and (7) deal with the validity intervals of fluents. In particular, predicate (5) specifies that a fluent F keeps value V for a time interval going from Tmin to Tmax if nothing happens in the middle that breaks such

an interval. Predicates (6) and (7) behave in the same way, but deal with open intervals.

The domain dependent predicates in EC are typically expressed in terms of the initiatesAt/2 and terminatesAt/2 predicates. One example of a common rule for initiatesAt/2 is

$$
\begin{aligned}
\text{initatesAt}(F = V, T) \leftarrow \\
\text{happensAt}(Ev, T), \qquad\qquad (8) \\
Conditions[T].
\end{aligned}
$$

The above definition states that a fluent is initiated to value V at time T if an event Ev happens at this time point, and some optional conditions depending on the domain are satisfied. In relation with MAGPIE, the agent platform in which the proposed agent mind has been integrated, these events that must happen are physiological measurements from the patient.

2.2 Cached Event Calculus and jREC

Straightforward implementations of EC [16] have time and memory complexity which are not practical for developing real applications. This is due to the fact that every time the EC engine is queried, the computation starts from scratch, and all fluents validity intervals are calculated again. Cached Event Calculus (CEC), proposed by Chittaro and Montanari [10], tries instead to overcome this inefficiency by giving EC a memory mechanism, and moving computation from query time to update time.

CEC formalizes the concept of Maximal Validity Interval (MVI), that represents a time interval in which a particular fluent holds without being terminated by any event. A fluent is also associated to a list of MVIs, in order to express all the time intervals in which that fluent holds continuously.

Whenever the rule engine is updated (e.g. by inserting a new event occurrence), the fluents' MVIs are calculated, and then stored for further use, allowing incremental computation for following updates. Also, every time a new event is added to the database, CEC manages to compute MVIs only for the fluents that can vary with that event, and does not check the MVIs of those fluents that cannot possibly change, thus avoiding unnecessary computation.

jREC is a reasoning tool based on Java and tuProlog that implements a lightweight version of CEC [4]. Since MAGPIE is also written in Java, it has been chosen to implement the proposed agent mind, in order to ensure seamless integration with the agent platform.

jREC consists of three main components:

- The Prolog theory, which represents the actual CEC axiomatization that is loaded into tuProlog;
- The Java engine, which allows to query and update the database without having to interact directly with tuProlog, as well as adding specific domain-dependent theories;

– The Tester, which is a GUI based stand-alone tool for editing theories, visualizing fluents' MVIs and event occurrences, mainly used for prototyping and developing domain-dependent theories.

3   System overview

The implemented agent mind runs in Tier-2 of the MAGPIE agent-based PHS for self monitoring of diabetes. The entire PHS is depicted in Figure 1. Each patient has its own agent composed by a body (Tier-1) and a mind (Tier-2) running on the personal server: in Tier-1 data are collected from the patients through a BAN; in Tier-2, the agent minds are responsible to trigger possible alerts based on the patients' physiological values, running domain dependent rules which could be customized for each patient. The triggered alerts have to be sent as a notification to medical doctors connected to Tier-3.
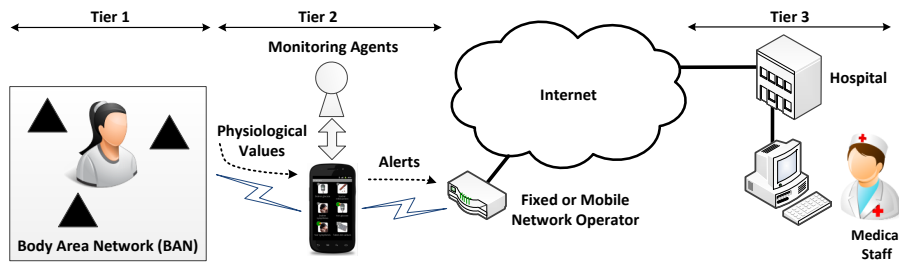

Fig. 1: The agentified PHS. The agent mind runs in Tier-2, to monitor the patient's physiological values.

3.1   MAGPIE Agent Platform

MAGPIE is an agent platform integrated with the Android OS. It plays the role of Tier-2 in a PHS by connecting the patient and the medical doctor, with the aim of improving the management of chronic diseases. From the side of the patient it collects physiological values, whereas from the medical side it models the medical knowledge in terms of monitoring rules expressed as domain dependent axioms of EC. Interested readers can find in [8] a description of the MAGPIE architecture and its integration with Android. In relation to this work, a monitoring rule is defined as a combination of events that trigger an alert to be notified to a medical doctor, where an event is considered as the measurement of a physiological parameter. Therefore, the following two types of monitoring rules are specified:

- Complex rules: consist of the combination of two or more events in a specific time window, where the order in which the events happen is not considered.
- Sequential rules: consist of the sequence of two or more events in a specific time window, where the particular order in which the events occur matters.

3.2 Diabetes Monitoring Rules

In order to detect alert conditions related to diabetes, a sequential and a complex rule patterns are proposed. These rule patterns are based on the literature available for glucose and blood pressure monitoring [12, 5] and checks physiological values collected by the patient's BAN. The patterns identify alert conditions in the patient's health status by modeling the sensor inputs as events that are evaluated in the body of the rules. The two patterns are:

Pattern 1: Brittle diabetes, defined as a glucose rebound going from less than 3.8 mmol/l to more than 8.0 mmol/l in a period of six hours. This pattern can be expressed with a sequential rule.

Pattern 2: Pre-hypertension, defined as two events of high blood pressure in a period of one week. This pattern can be expressed with a complex rule.

Pattern 1 is implemented as follows:

$$\text{initiatesAt}(F = A, T) : -$$
$$\text{happensAt}(\text{ev}(2, A, W), T),$$
$$\text{happensAt}(\text{ev}(1, A, \_), T_1),$$
$$T_s \text{ is } (T - W), \tag{9a}$$
$$T > T_1,$$
$$T_1 >= T_s,$$
$$\text{no\_alert}(A, T_s).$$

$$\text{terminatesAt}(F = A, T) : -$$
$$\text{happensAt}(\text{ev}(1, A, \_), T). \tag{9b}$$

$$\text{happensAt}(\text{ev}(1, \text{'brittle diabetes'}, E), T) : -$$
$$\text{hours\_to\_epoch}(6, E),$$
$$\text{happensAt}(\text{glucose}(G), T), \tag{9c}$$
$$G =< 3.8.$$

$$\text{happensAt}(\text{ev}(2, \text{'brittle diabetes'}, E), T) : -$$
$$\text{hours\_to\_epoch}(6, E),$$
$$\text{happensAt}(\text{glucose}(G), T), \tag{9d}$$
$$G >= 8.$$

Rules (9a) and (9b) represent a generic sequential rule template with two events. In particular, the fluent F (i.e. the alert) is initiated with value A when: (i) two temporal ordered events occur inside a certain time window and (ii) when

the fluent does not hold anywhere else inside the time window (no_alert/2). The fluent F is instead terminated when the first event of the ordering happens.

Rules (9c) and (9d) customize the template for the glucose monitoring use case. They instantiate the variables of the ev/3 term, specifying the time window width (W), the alert name (A) and the threshold values for G.

Pattern 2 is expressed in the following way:

$$\text{initiatesAt}(F = A, T) : -$$
$$\text{happensAt}(\text{alertcheck}(A, W, NMax_1), T),$$
$$T_s \text{ is } (T - W),$$
$$\text{count\_events\_tw}(N_1, \text{evc}(1, A), T_s, T), \qquad (10a)$$
$$N_1 >= NMax_1,$$
$$\text{no\_alert}(A, T_s).$$

$$\text{terminatesAt}(F = A, T) : -$$
$$\text{happensAt}(\text{alertcheck}(A, W, \_), T), \qquad (10b)$$
$$\text{holdsAt}(F = A, T).$$

$$\text{happensAt}(\text{evc}(1, \text{'pre-hypertension'}), T) : -$$
$$\text{happensAt}(\text{blood\_pressure}(S, D), T),$$
$$S >= 130, \qquad (10c)$$
$$D >= 80.$$

$$\text{happensAt}(\text{alertcheck}(\text{'pre-hypertension'}, E, 2), T) : -$$
$$\text{weeks\_to\_epoch}(1, E), \qquad (10d)$$
$$\text{happensAt}(\text{evc}(1, \text{'pre-hypertension'}), T).$$

Rules (10a) and (10b) represent a generic complex rule template with one event type. In particular, the fluent F (i.e. the alert) is initiated with value A when: (i) there are least $NMax_1$ occurrences of the alertcheck/3 event inside the time window and (ii) when the fluent does not hold anywhere else inside the time window (no_alert/2). Also, the count_events_tw/4 predicate is necessary to handle different event temporal orderings without having to duplicate the rule body for every permutation. Rules (10c) and (10d) customize the template for the hypertension monitoring use case. They instantiate the variables of the evc/2 and the alertcheck/3 terms specifying the time window width (W), the alert name (A) and the threshold values for S and D.

4 Test setup and results

The performance of the jREC agent mind has been evaluated using the sequential and complex rule patterns described above. To accomplish that, synthetic datasets containing glucose and blood pressure measurements have been created. Each measurement is a tuple containing the value(s) and its timestamp.

4.1 Testing Protocol

To see how the performance of the agent mind evolves when the number of events increases, a series of random dataset has been created, each one containing a different number of events.

The events of each dataset are fed into the agent mind one by one, and the time needed by the agent to trigger the alert is recorded. Each experiment is repeated one-hundred times to obtain the mean and standard deviation values.

The biggest assumption of the experiment is that real datasets do not add any value to the performance evaluation. In fact, the use of synthetic datasets allowed to stress the agent minds on very specific and critical tasks.

4.2 Results and Discussion

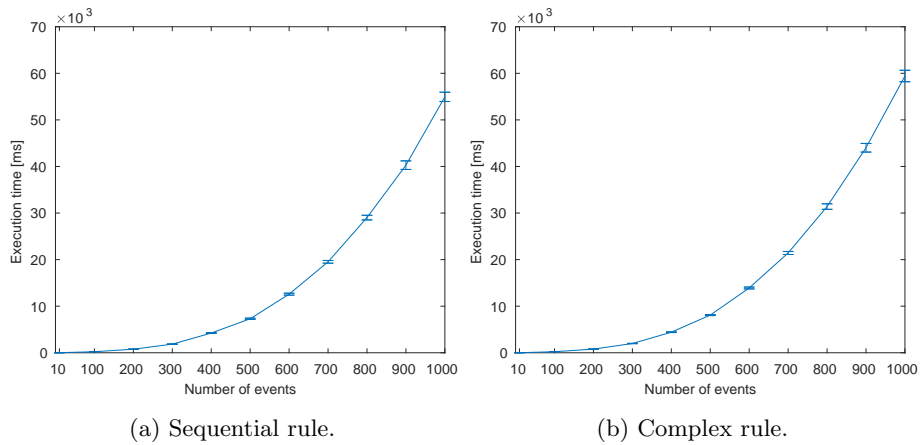(a) Sequential rule.   (b) Complex rule.

Fig. 2: Milliseconds needed by the JREC agent mind to compute an alert, for the different rules.

The tests have been executed on an i7-6700K@4.20 GHz CPU with 16 GB@2400 MHz DDR4 RAM, running Ubuntu/Linux 16.04 and Java Runtime Environment 8u121.

It should be noticed that the main results of these tests are the execution time trends, rather than the absolute values themselves (since they vary with different machines). From plots in Figure 2a and 2b, it is clear that the execution time grows in a polynomial fashion. Thus, feasibility of the reasoning performed by the agent mind must be evaluated carefully depending on how many events are expected to occur, and on the time constraints in which the alert must be generated.

With the machine used for tests, it is shown that keeping the event number less than 500 would lead to a reasonable computation time. Thus, some possible

real-case applications for the jREC agent mind, with the proposed rule patterns, can be:

– Detecting Brittle Diabetes with Continuous Glucose Monitoring devices. They can provide glucose measurements up to one minute [12], so referring to the Rule Pattern 1, it would mean a worst case scenario of 360 events.
– Detecting Pre-Hypertension conditions with digital arm sphygmomanometers. It is enough to have two blood pressure measurements per day [5], so referring to Rule Pattern 2, it would mean a worst case scenario of 14 events.

5 Related work

Multi-Agent Systems (MASs) meet the requirements of the healthcare sector: context awareness, reliability, data abstraction and interoperability, unobtrusiveness [3]. From a requirements engineering perspective, goal-oriented and agent-based design methodologies are useful to tailor pervasive systems to end-users and stakeholders' needs [9]. When appied to PHSs, agent-based modeling has the potential to bring the decision making at the level of self-management of chronic diseases [17]. In the implementation phase, MASs in PHSs pursue the enhancement of home-based self-care by using networks of sensors and remote assistance, to increase the satisfaction of the patient and make an efficient use of resources [13].

Reasoning agents in PHSs allow to transfer part of the knowledge from domain experts to the handheld devices used to perform the self-management of chronic diseases. Beyond PHSs, other applications include energy management [21], to control energy demand and production, home automation [22], to coordinate the available appliances, and ambient assisted living [19, 23], with monitoring purposes. In the context of PHSs, EC and MASs have been successfully applied to the self-management of diabetes [15, 6]. However, such works do not take into account the scalability of the PHS. In fact, a clear advantage of reasoning agents in the Tier-2 of PHSs is the system scalability with increasing number of patients, as showed in [7]. Nevertheless, in such research, the scalability of the agent minds with high streams of events is not considered. Thus, there is the need to find the suitable tools to implement agent minds, which are supposed to run in portable devices, even with high numbers of events and large datasets. This is especially true for EC given its complexity. Indeed, non-logic based pattern recognition has been proved, overall, more efficient than traditional EC when performing predictions. However, it lacks the potential of coding domain experts' knowledge into logic rules and needs to train on large amounts of data. Hence, caching and windowing techniques to make EC efficient and applicable with large scale dataset have been investigated [4, 1]. There are some already available tools that allow logic programming in terms of EC. One of such is DECReasoner [18], a Discrete Event Calculus Reasoner: it implements EC without any caching mechanism and, thus, it is not usable for this research, due to its computation time with the datasets used for the performance tests. A

more efficient EC implementation is RTEC, which adds to EC support for handling event streams [1]. However, it is not compatible with the agent-oriented PHS considered in this research, which is based on tuProlog and Java [7]. Thus, jREC has been used to implement a prototype for the proposed agent mind, since it implements Cached Event Calculus [4] with tuProlog, a Java-based Prolog engine [11]. Moreover, being Java-based, jREC and tuProlog can run on Android devices, allowing to run the proposed agent mind on handheld devices.

6   Conclusions

In this work, a rule-based mind for monitoring agents running on Tier-2 of a PHS has been presented and tested. It is based on jREC, a CEC reasoner. In order to be used in real monitoring scenarios, the agent mind has to be able to process high stream of events, represented by the patient's physiological values. Therefore, the main contribution of this paper is the evaluation of the performance of the proposed agent mind on the time needed to trigger alerts based on glucose and blood pressure levels, in a diabetes monitoring scenario. The results show that a reasonable computation time can be obtained with less than 500 events occurrences. Two real application scenarios for the proposed agent mind are the detection of brittle diabetes, with Continuous Glucose Monitoring, and the detection of Pre-Hypertension conditions, with devices such as digital arm sphygmomanometers.

As future work, since PHS is intended for the self-management of diabetes with a handheld device, the tests should be performed on mobile phones, to obtain more realistic figures. In this direction, work must be done to improve the agent mind efficiency, to get a lower execution time with higher number of events. Furthermore, in order to validate the usefulness of the rules, the tests should run on real datasets. Lastly, the system can be applied to other use cases, in order to model rules for other diseases.

Acknowledgments

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