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Towards a cognitive engineering of transactional services in IoT based systems☆

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ABSTRACT

Cognitive computing is the capability of a system to mimic the ability of human brain to learn and adapt from the surroundings. Cognitive systems have decision-making capabilities based on new information, actions and outcomes. Similarly, Internet of Things (IoT) aims at making things smart, and enabling them to perform complex tasks. Reliability and flexibility are persistent challenges in the IoT context where the promise is managing a multitude of devices and delivering real-time responses for critical smart applications. A limited number of studies examine these challenges while considering cognitive capabilities of things and have failed to handle thing's specificities in terms of communication bandwidth, power availability and storage capacity. Following the service oriented architecture (SOA), the functionality can be encapsulated as services. Thus, automating the management of transactional services in smart IoT ecosystem can be fulfilled through the coupling of transactional properties to cognitive things. This paper provides a comprehensive approach to alleviate reliability restrictions in cognitive IoT service compositions. The concept of cognitive faculty (CF) is introduced to leverage transactional properties of services and can be customized to specific requirements of IoT applications. A proof-of-concept is included in this paper based on a self-monitoring IoT application for diabetic patients.

1. Introduction

The progress in the fields of artificial intelligence, machine learning and Internet-of-Things (IoT) has allowed developing cognitive systems that anticipate the IoT challenges (Sheth, 2016). According to Whitmore et al. (2015), IoT is "*a paradigm where everyday objects can be equipped with identifying, sensing, networking and processing capabilities that will allow them to communicate with one another and with other devices and services over the Internet to achieve some objective*". In line with this definition, a "*thing*" is any object equipped with some communication capabilities. The blend of cognitive capabilities with IoT would result into Cognitive Things. Cognitive Internet-of-Things (CIoT) is brain-empowered IoT (Wu et al., 2014). In CIoT ecosystem, we can identify the source of potential problems before they even arise and react as quickly as possible to ensure maximum efficiency (Zhang et al., 2012; Franklin et al., 2014; Vanus et al., 2017).

Beyond device connection and connectivity, IoT has three main features related with the DIKW (data, information, knowledge, wisdom) model (Baskarada and Koronios, 2013), which consists of transforming data into knowledge, actions and decisions. These noteworthy features are data sensing and collecting, data analysis to define actions, and data transport and access (Mzahm et al., 2013). From SOA perspective, processing data functionalities can be encapsulated as services and complex tasks can be fulfilled through composite services. Since IoT applications are context-dependent, too monolithic and silos-oriented, which prevents flexibility and hampers customization (Mihailescu et al., 2017), the composition should incorporate only the services that the user needs and thus, would gain in reliability and performance. Furthermore, things are typically considered as data providers, and hence, their active nature is distorted by omitting their actionable intelligence (Pourghebleh et al., 2022). These concerns are augmented with adaptability issues in existing IoT architectures that do not offer a loose coupling of the components allowing a recomposition, depending on behavioral changes during stream processing (Persson and Angelsmark, 2015; Global Sensor Networks, 2014; Node-RED, 2018; Paraimpu, 2018).

This paper deals with three main challenges in the development of IoT applications based on cognitive capabilities, including, adaptability, reliability and self-awareness. Cognitive things should have the ability to learn, interpret, negotiate, predict, and control on the fly. A real-time coordination among sensing and actuation devices is a prior condition to proactive decisions. Adaptability around self-healing of resources, changing

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the resource state, reconfiguration due to environment fluctuations is limited in the existing IoT network service compositions (De Sanctis et al., 2021; Alkhabbas et al., 2020). Reliable executions in IoT service compositions are crucial particularly in safety-critical applications. IoT reliability is restricted mainly since things act, as silos independently from each other. This is accentuated by the fact that IoT devices are heterogeneous in terms of resource capabilities, life span and communication capabilities. Self-awareness is another factor that must be considered for smart IoT systems based on cognitive features where humans have less control. Things should shift their role from passive data suppliers to self-managed entities in terms of resource consumption, actuation, and situation recognition. A mission-critical IoT application involving medical wearables needs to rely on self-aware objects that can take specific actions and determine incessantly fault tolerant mechanisms in the case of an incident. Empowering the reliability, adaptability, and self-awareness of IoT service compositions is critical to fostering the concept of Cognitive things.

Although huge efforts have been made to tackle each requirement separately (Angarita, 2015; Dias et al., 2020; Maamar et al., 2020; Vidyasankar, 2016), current approaches are not sufficient to address the problem complexity imposed by the convergence of the physical and intelligence spheres. Designing a reliable smart IoT system requires a broad approach that considers cognition, the requirement of distributed intelligence, and heterogeneous yet autonomous objects.

To address the aforementioned issues, we examine the coupling of transactional properties to cognitive things. El Haddad et al. (2010) considers three types of transactional properties. An operation or by extension a service performing a task can be: (i) compensable: the results produced by the task can be canceled, (ii) retriable: the task ends successfully after a finite number of invocations, and (iii) pivot: the task cannot be compensated or re-executed. The retriable property can be combined with the other properties. Thereby, we can define four transactional properties of things: retriable, compensatable, compensatable retriable and pivot retriable. Injecting these properties into things guarantees reliable IoT compositions and allows to define recovery mechanisms and minimize failure events.

Our contribution is threefold: (i) defining cognitive capability (faculty) of things, (ii) empowering the CF with transactional properties (TP), (iii) selecting the appropriate CF/TP combination to align with CIoT features and to adapt to a variety of IoT scenarios. The remainder of this paper is organized as follows. Section 2 presents related works. A motivating case study is introduced in Section 3. Section 4 highlights the proposed approach in terms of defining and selecting cognitive faculties and transactional properties and coupling them to things. Section 5 exhibits the system model that addresses composition requirements in cognitive-based transactional IoT services. Section 6 carries out some experiments and evaluation. Finally, we conclude and present future works in Section 7.

2. Literature review

There have been several attempts in the literature focusing on IoT architectures. In this article, we are particularly interested in studying cognitive-based IoT systems and works that evince benefits of using transactional properties in IoT. In the following, we discuss related works in the scope of CIoT architectures and transactional IoT systems.

2.1. Cognitive IoT architectures

Mostly all CIoT platforms focus on the same issues namely homogenizing and transforming things to more autonomous and intelligent entities. In Reisenzein et al. (2013) research, semantic information and cognition are introduced in IoT applications to improve intelligence. Foschini et al. (2011) introduce the Smart City Network based on a CIoT architecture with three key components, namely, sensor, machine learning and semantic modeling components. Vlacheas et al. (2013) propose a cognitive management framework which identifies and connects things that are relevant to the application. The work of Maamar et al. (2018) suggests incorporating cognitive capabilities to things which participate in ongoing business processes (BP) that have to interact with, thus cannot be considered as a CIoT ecosystem, since BP are not acting upon things or directing them. Sensors and actuators form the key elements of IoT. Their network is generally composed of a potentially large number of nodes. These sensors have to deal with many communication issues such as their mobility, short range, reliability, robustness, scalability and resources (i.e., energy, limited storage and processing capacity, bandwidth, etc.). As a result, new paradigms have emerged. Things as-a-service (Distefano et al., 2012) aggregates and abstracts heterogeneous resources according to a personalized thing semantic. Sensor as-a service (SenaaS) (Zaslavsky et al., 2013) allows ubiquitous management of remote sensors. IoT Mashup-as-a-Service (IoTMaaS) (Janggwan et al., 2013) is proposed to comply with device heterogeneity by following model-driven architecture (MDA) principles. MOSDEN (Perera et al., 2014) is an IoT middleware for mobile device with limited computational resources. It allows to collect data from several different sensors and process them together. However, sensor discovery and service composition are not automated. The problem is that many CIoT ecosystems rely on centralized communication models. A distributed service-oriented approach would solve this issue by distributing computing and storage needs among the billions of things. Things should be interoperable and composable. None of the aforementioned approaches is both dynamic, decentralized, covering non-functional and structural constraints and incorporates self-monitoring mechanisms. A conceptual framework for Internet of Behavior system design is presented in Moghaddam et al. (2022). The work proposed by Moghaddam et al. (2022) deals with QoS issues linked with human behaviors, as adaptations are based essentially on perceived human behavior, and hence, the proposed system could not be labeled as a cognitive IoT platform. Similarly, De Sanctis et al. (2021) introduces a multi-level adaptation architecture for microservices-based IoT applications. The adaptation is performed according to user's goals and supports better management of QoS at multiple levels. However, adaptations are not proactive and the whole system lacks cognition. Authors in Alkhabbas et al. (2020) addresses emergent configurations in IoT environments in order to ensure dynamic adaptation considering several requirements. Although the approach is interesting, it fails to enhance cognition and autonomy of things and focus solely on context-awareness aspects that remain outside the scope of this paper.

2.2. Transactional IoT approaches

Transactional properties are primarily used in fault tolerance mechanisms for defining execution behaviors of a computational unit in term of success or failure. Very few works has considered transactional properties in IoT. In this section, we present approaches that addresses fault tolerant issues regarding reliability and adaptability aspects in IoT ecosystem. KASOM (Corredor et al., 2012) is a service-oriented and knowledge-aware middleware.

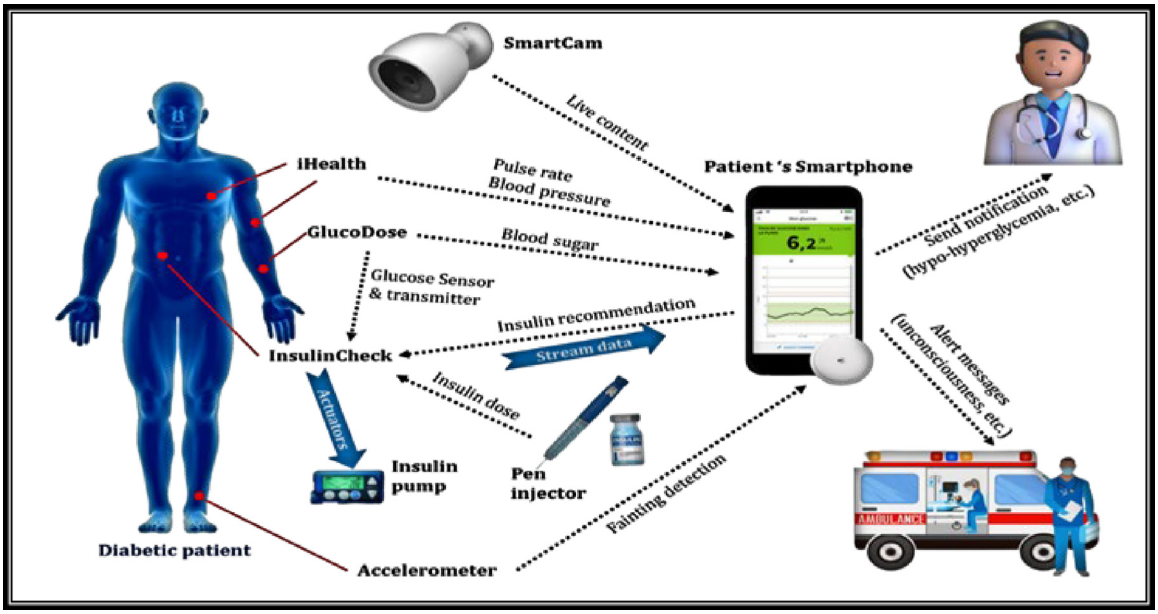

Fig. 1. IoT architecture of the self-monitoring system.

It enables discovery, orchestration and composition of services and has shown good results in terms of reliability, efficiency and response time. However, due to predefined service composition rules, it does not provide dynamic service composition in IoT infrastructures. Dias et al. (2020) present a set of patterns for self-healing IoT systems. These patterns can improve system reliability by providing error detection, error recovery, and health mechanisms maintenance. Although these works suggest solutions to IoT reliability and adaptability, they need to leverage the bend of transactional properties to things for reliable execution of service composition. For instance, works like Angarita (2015), Vidyasankar (2015, 2016), Maamar et al. (2020) target transactional properties in IoT. Angarita (2015) emphasizes the role of transactions for self-healing IoT applications. The authors introduced the concept of responsible things which combines transactional and self-awareness properties. In Vidyasankar (2015, 2016), the author defines ACID properties of IoT service compositions namely atomicity, retriability, compensatability, and pivot to verify IoT service execution. To refine the transactional properties that should be used to adapt to various IoT applications, the authors suggest triggering and continuous execution. The work of Maamar et al. (2020) exhibits the importance of transactional analysis of things for IoT reliability. The authors suggest to associate transactional properties with IoT basic duties (i.e., sensing, actuating, communicating). However, the work does not consider enriching things with cognitive capabilities. Despite introducing the concept of transactions for self-healing IoT applications, these works focus solely on treating things as concurrent transactions; our work envisages empowering cognitive capabilities of things with transactional properties to achieve reliable service compositions.

The literature review resulted into a very limited number of works on CIoT adaptability and reliability. To the best of our knowledge, there are no available approaches that deal with the adaptability, reliability and self-awareness of things and that combine cognition and transactional behaviors while designing IoT service compositions.

3. Case study

We motivate our work through a self-monitoring IoT application for high-risk diabetic patients. Diabetes is a data pathology. Data is collected via blood sugar sensors connected to a smartphone. The device implanted in the patient is associated with a continuous glucose sensor and an insulin pump. A blood sugar sensor stream data every 5 min. The device evaluates the level of blood sugar to alert the patient that he must inject himself within 30 min. The idea is to calculate constantly, and in advance, the blood sugar level that the patient will have in two hours, in order to determine how much insulin he needs immediately. A cap object automatically collects in real time the insulin doses selected by the patient during his day from the connected insulin injectors. A smart device for sensing the vital parameters of the patient is used to warn professionals in the case of hypoglycemia or hyperglycemia in order to check the patient's condition. This device is supported by a shock sensor and smart cameras installed in the patient's home. These sensors will allow to alert the paramedical at the appropriate time in the event of an accident or a fall of the patient. The data captured by these objects are sent to the patient's Smartphone. An automatic analysis tool is integrated to alert the professional in the event of abnormalities (e.g., hypo or hyperglycemia) that are too frequent. Several different alert messages are defined. Fig. 1 shows the IoT architecture of the self-monitoring system.

We assume that mostly marketed IoT systems for diabetes evolve mainly sensing functionalities. The sensors would alert patients of any blood sugar abnormalities before it leads to hypoglycemia or other critical conditions. However, by the time the sensor notices the patient, it could be too late if it detects a higher or lower levels of blood sugars. Therefore, sensors should operate in a closed loop fashion with actuators (i.e., intelligent insulin pump) that can automate and personalize the delivery of insulin through a self-learning machine system. Our proposal is to equip all involved devices with cognitive functionalities in order to reason about sensed data and to avert possible disruptions due to resource consumption or services' unavailability that could be disastrous for life-saving systems.

4. Merging transactional properties into cognitive things

4.1. Cognitive faculties of things

The abundant literature of Cognitive Computing propose a multitude of cognitive systems definition. In this paper, we refer

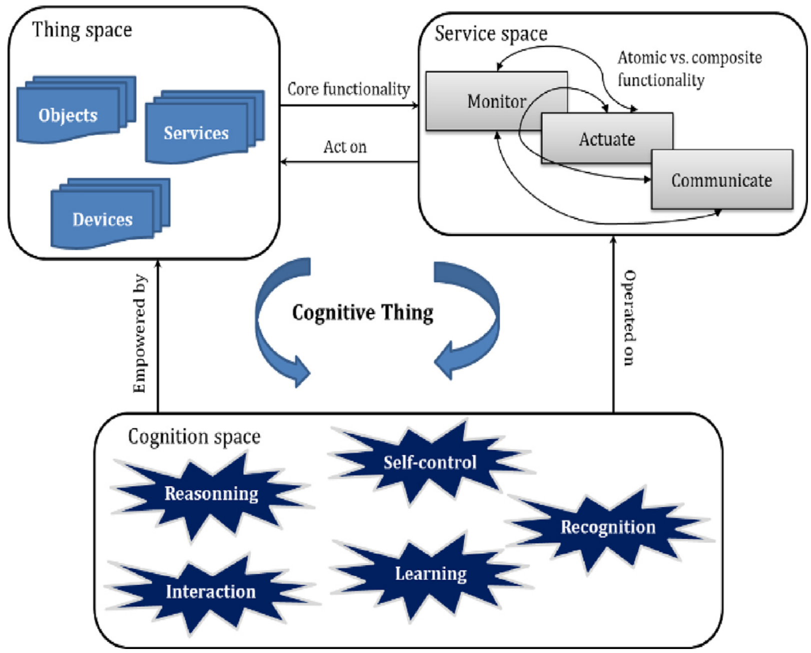

Fig. 2. The perception of a Cognitive Thing.

to Johnson's definition of a cognitive system as "*a system that can reason, use represented knowledge, learn from experience, accumulate knowledge, explain itself, accept direction, be aware of its own behavior and capabilities as well as respond in a robust manner to surprises*" (Johnson, 2002). In IoT ecosystem, monitoring, actuation, and communication are key functionalities, which are basic things responsibilities. Hence, things should be augmented with cognitive capabilities. We introduce the concept of cognitive faculty. If we look up the definition of faculty in the Merriam Webster Dictionary, we get the following definitions: (i) innate or acquired ability to act or do, (ii) an inherent capability, power, or function, (iii) any of the powers of the mind (such as will, reason, or instinct) formerly held by psychologists to form a basis for the explanation of all mental phenomena, (iv) something in which one is trained or qualified. In correlation with the above definitions, we identify five main CF that characterize things. Fig. 1 shows the possible interactions among things and their CF.

Each CF acts upon one or multiple IoT features (i.e., monitor, actuate, and communicate). Things can achieve either atomic functionality as well as composite features, namely: (1) Monitor, Actuate, then Communicate; (2) Monitor, then Communicate; (3) Monitor, then Actuate; (4) Actuate, then Communicate; (5) Communicate, then Actuate; (6) Communicate, Actuate, then Monitor. In this particular study, we assume that things could encompass one specific functionality. Following this distribution, each CF can be enabled or disabled on IoT features.

Hence, we introduce the REASON model (Reasoning rEcognition interAction Self-cOntrol learNing), in which we specify five cognitive faculties that could be enabled on IoT basic functionalities. As displayed in Fig. 2, Interaction is a CF that acts upon Communicate feature. For a thing to interact with the surrounding (i.e., services, devices, objects, etc.), it uses communicating functionality to ask for specific information and to transfer data. Reasoning is a CF that acts upon Actuate feature. Reasoning is an inherent capability of cognitive things, it serves the actuating functionality by providing necessary information to trigger relevant data. Recognition is a CF that could be enabled on both Monitor and Actuate features. The objective is to enrich things with pattern recognition functionalities in order to process the data captured in the monitoring stage-in this case, recognition CF is enabled on monitoring functionality- or to proceed to raw data processing at the actuating level on which recognition should be enabled. Learning is a CF that could be enabled on Actuate feature. The amount of knowledge that has been produced throughout data triggering will help the actuating phase to learn while providing accurate actions. As for Self-control CF, it should be enabled on all IoT features (i.e., Monitor, Actuate, and Communicate). A cognitive thing must comprehend self-controlling properties. By self-control, we refer to the ability of a thing to adjust its behavior as a response to unreliable environment executions and in the presence of potential failures. Therefore, things should continually monitor the following parameters:

Table 1
Enabling/disabling CF on thing's atomic features.

Cognitive faculty	Thing's atomic features		
	Monitor	Actuate	Communicate
Reasoning	Disabled	Enabled	Disabled
Recognition	Enabled	Enabled	Disabled
Interaction	Disabled	Disabled	Enabled
Self-control	Enabled	Enabled	Enabled
Learning	Disabled	Enabled	Disabled

- Resource consumption: cognitive things should be aware of their resource consumption in terms of communication bandwidth for data transfer, power availability for a specific operation, storage capacity, and so on.
- Processing power: a cognitive thing should be aware of the number of instructions it can process in order to avert failures and execution delays.
- Response time: while performing a specific feature, a cognitive thing should be aware of runtime and progress execution details to minimize the task response time accordingly.

Table 1 summarizes Cognitive Faculties that could be activated on each IoT functionality, namely, Monitor feature, Actuate feature, and Communicate feature.

Table 2
The validity of transactional properties on thing's CF and thing's AF.

Thing's atomic features/Thing's cognitive faculties	Transactional properties				
	Pivot	Retriable	Compensatable	Pivot-retriable	Compensatable-retriable
Monitor	x	+	x	x	x
Actuate	x	+	+	x	+
Communicate	x	+	x	x	x
Reasoning	x	+	+	x	+
Recognition	x	+	x	x	x
Interaction	x	+	x	x	x
Self-control	+	+	x	+	x
Learning	+	+	+	+	+

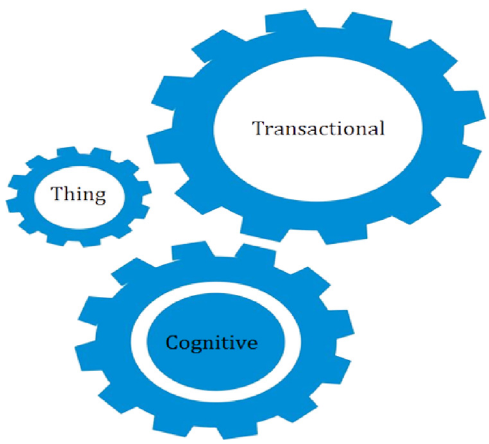

Fig. 3. Merging transactional properties into cognitive things.

4.2. Empowering CF with transactional properties

As mentioned earlier, transactional properties are mainly used to guarantee IoT applications consistency and reliability in presence of failures. In this paper, we exploit transactional properties to empower cognitive things with recovery mechanisms provided by the following properties: (1) pivot, (2) retriable, (3) compensatable, (4) compensatable-retriable, (5) pivot-retriable. Fig. 3 illustrates the coalition of three ecosystems, which deliver fault-tolerant cognitive things.

We examine minutely the convenience of assigning each transactional property to a cognitive faculty and the appropriateness of associating these properties to atomic features (AF) of things.

- Pivot: The pivot property should not be assigned to Monitor or Actuate features, since an uncompleted monitoring or failed actuating impacts captured and actuated data which are very crucial to the functioning of every IoT application. It should not be assigned to Communicate feature as well, insofar as data communication is the backbone of IoT ecosystem. Pivot is not either appropriate for CF such as Reasoning, Recognition, and Interaction. Depriving Actuate feature from inferred data due to a failed or uncompleted reasoning operation will impact the correctness of the triggered data and possibly bias the whole system outcome. Similarly, a failed pattern recognition would result in retracting an essential cognitive capability which assists Monitor and Actuate operations in processing raw data quickly and accurately. Furthermore, a failed or uncompleted interaction with external parties would cause system's deadlocks and inconsistent states and disable Communicate feature due to truncated information. Contrariwise, pivot can be tolerated for Learning and Self-control faculties. Indeed, a failed learning operation or an unsuccessful self-controlling task should not jeopardize the functioning of the IoT application.
- Retriable: Retriable property must be assigned to each CF/AF in the sense that real-time updated data should be available throughout the data lifecycle at all execution levels of the IoT application (i.e., recognizing, monitoring, reasoning, actuating, interacting, learning, communicating, self-controlling).
- Compensatable: Compensatable property is acceptable for Actuate feature. Indeed, in case of a failed actuating operation, actuating actions should be reversed. However, it is not applicable for Monitor feature, since compensating monitoring actions is not feasible. It should not be assigned to Communicate feature as well, in the sense that communicating effects cannot be semantically undone. Identically, compensatable property cannot be applicable for CF such as Recognition, Interaction and Self-control as their effects do not need to be undone, whereas it is acceptable for Reasoning and Learning to be compensatable.
- Pivot-retriable: the validity of this property vis-a-vis the CF/AF is deduced from the study conducted on the pivot, retriable and compensatable properties.
- Compensatable-retriable: the validity of this property vis-a-vis the CF/AF is deduced from the study conducted on the pivot, retriable and compensatable properties.

Table 2 exhibits the applicability of transactional properties towards Cognitive Faculties and atomic features of things. We use the following notation: (x) refers to not applicable and (+) refers to acceptable.

4.3. Holistic approach overview

As mentioned earlier, a cognitive IoT based application should operate in a distributed fashion where thing's functionality can be encapsulated as service. Hence, task functionalities may involve multiple things and could be executed through service composition. The overall approach relies on injecting cognitive capabilities into things while providing application reliability and adaptability in presence of failures. These can be guaranteed through recovery mechanisms by merging transactional properties to cognitive things. Fig. 4 exhibits the general approach to guarantee reliability in smart IoT applications. A cognitive IoT application involves three components, activation, diagnosis, and adaptation.

The activation component enables cognitive faculties on atomic features from a repository of things that will participate in the IoT application (Cf. Section 4.1). According to the IoT designer needs in terms of application semantics, the activation component selects the appropriate cognitive faculties as per the REASON model (not necessarily all) to enable on each thing's feature (i.e., sensing, actuating, and communicating). For the diabetes monitoring system, the SmartCam sensor object should be augmented with pattern recognition capabilities to detect instantly any unusual patient condition. In other less-critical IoT applications, the recognition faculty could be disabled for

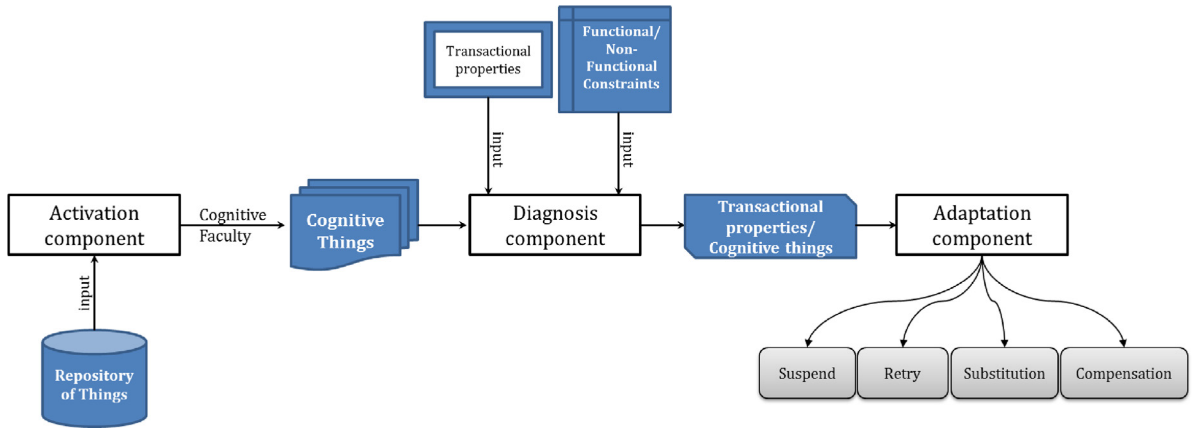

Fig. 4. Holistic approach for cognitive IoT-based application reliability.

the SmartCam object. Prior to enabling a cognitive faculty, the activation component is responsible for checking the appropriateness of activating a CF on a thing feature, even if it conflicts with the IoT designer requirement. For instance, reasoning or learning CF cannot be activated on objects that are mainly interacting (transferring data) with other parties (i.e., communicating feature).

The diagnosis component analyzes functional and non-functional constraints in order to enact the appropriate transactional properties. Functional constraints are related to the applicability of transactional properties regarding a semantic functionality of thing (Cf. Section 4.2). For instance, in a transportation emergency system, a traffic barrier cannot be considered pivot since its failure can give rise to system's deadlocks. SmartCam and Accelerometer could be switched on and off, since it does not affect considerably the patient's condition in most cases, thus, ambient sensors are considered pivot. GlucoDose, iHealth sensors streams vital data to the Smartphone analyzer, therefore are considered retriable. Non-Functional constraints include persistence, computation and communication capabilities of cognitive things and refer to the availability of similar things. For instance, a diabetic patient that has an implanted device to measure blood sugar levels should be equipped with a substitute one in case the operational device has volatile memory. Thus, in this particular situation, it is not acceptable to assign the retriable property to the blood sugar monitoring device. Prior to merging transactional properties with cognitive things, the diagnosis component evaluate the validity of assigning a transactional property to a particular thing. This inspection is conducted on two basis in different timelines: (i) in accordance with IoT application semantics (i.e., functional constraints) at design level before the TP/CT merging operation and (ii) depending on the availability of cognitive things at run-time which is ensured by the self-awareness capability (which should be enabled on all participating things) that allows the thing to self-monitor persistence, computation, and communication settings (i.e., non-functional constraints).

The adaptation component is responsible for selecting and performing the appropriate recovery mechanism according to the transactional properties, event failures, and behavior degradation. Recovery mechanisms are mainly ensured by compensation, substitution, retry and execution delay or by suspending the activity of the cognitive thing. The selection of the recovery option is dictated by the presence of substitute/redundant objects (i.e., forward substitution, preventive replication) and the enabled transactional properties (i.e., backward compensation, forward retry). Through the self-controlling CF, the adaptation component can switch on/off the participating objects according to their computational status by suspending their activity (i.e., checkpointing).

Notice that InsulinCheck and GlucoDose are vital devices for the diabetes monitoring system, hence, they should be enhanced with self-controlling capabilities to trigger a recovery mechanism in case of potential failures. Let us assume that InsulinCheck device fails to unlock insulin injector after a number of alert messages due to very high levels of blood sugar. Since it is retriable, multiple retries are performed to actuate the insulin pump, however, the device notices that it will take too much time using self-controlling capabilities; therefore, it interacts with other replicate objects (i.e., similar wearable devices) to perform actuations. Table 3 describes succinctly the proposed approach by merging transactional properties to cognitive objects of the self-monitoring IoT application for diabetic patients.

5. Composition requirements in cognitive-based transactional IoT services

As described in the proposed approach, an IoT application may involve multiple things where thing's functionality can be encapsulated as service. Thus, a cognitive IoT based application scenario can be considered as an abstract service composition SC (TF, $\prec$f), where TF is a set of thing's features $\{TF_1, TF_2, \ldots, TF_n\}$ and $\prec$f is a partial order among them. In the following, we use the notational conventions:

- S is the repository of services.
- s denotes an atomic or composite service.
- TF represents the core functionality of a thing. In this particular composition problem, we consider the thing's features as individual atomic capabilities.
- NP denotes a non-functional property of a composite service that must be satisfied by composing one or multiple services available in the set S. In our problem formulation, NP is represented by the set of cognitive faculty (CF) and the set of transactional property (TP) that are defined for a particular representation of things.
- $\otimes$ is a generic composition operator.

  Prior to exploring composition requirements induced by merging cognition and transactional properties into things, we start by giving a formal definition of a non-functional property.

Definition 1. A non-functional property specification is a Boolean combination of $\{\varphi_1, \ldots, \varphi_n\}$ where:

- φ_i is a tuple <{CF, TP}, TF>
- CF is an atomic or composite cognitive faculty which is applicable regarding the core functionality of a thing.

Table 3
Succinct illustration of the approach by merging the transactional properties to the cognitive things of the self-monitoring IoT application.

Objects	Service functionality	Cognitive faculties	Transactional properties	Recovery mechanisms
GlucoDose	Sense data Store data	Learning Self-control	Compensatable Retriable	Compensation Retry
InsulinCheck	Actuate data Store data	Interaction Learning Self-control	Compensatable Retriable	Substitution Compensation Retry
Smartphone	Send message Analyze data Store data	Interaction Learning Reasoning Self-control	Pivot Retriable	Retry
iHealth	Sense data Analyze data Store data	Learning Self-control	Compensatable Retriable	Compensation Retry
SmartCam	Sense data Analyze data Store data	Recognition Self-control	Pivot	Suspend Substitution
Accelerometer	Sense data Analyze data Store data	Recognition Self-control	Pivot	Suspend Substitution

- and TP is an atomic or composite transactional property which is valid vis-à-vis the core functionality of a thing.

For instance, InsulinCheck actuation capability is represented by the following tuple <{Learning, compensatable, retriable}, actuate data> which indicates the applicable properties (i.e., cognitive and transactional ones) regarding the actuation thing's feature.

Following this definition, the execution of an abstract service composition requires running some cognitive functionality along with some specific recovery mechanism, which is selected according to transactional properties. Therefore, we define a composite cognition denoted as CG (CS, $\prec$c) where CS is a set of cognitive services $\{CS_1, CS_2, \ldots, CS_m\}$ and $\prec$c is a partial order among them. Similarly, we define a set of transactional services denoted as T (TS, $\prec$t) where T is a composite transaction, TS is a set of transactional services $\{TS_1, TS_2, \ldots, TS_k\}$ and $\prec$t is a partial order among them. We give below the formal definition of a composite cognition, a composite transaction and an abstract service composition in the context of cognitive IoT applications.

Definition 2. A composite cognition CG of an abstract service composition SC is $(\{CS_1 \otimes CS_2 \otimes \cdots \otimes CS_m\}, \prec c)$, where each CS_i is an atomic service represented by an ordered set of operations which has inputs $In(CS_i)$, and outputs $Out(CS_i)$.

$$CS_i = (s, In(CS_i), Out(CS_i))$$

Definition 3. A composite transaction T of an abstract service composition SC is $(\{TS_1 \otimes TS_2 \otimes \ldots, TS_k\}, \prec t)$, where each TS_j is an atomic service represented by an ordered set of operations which has inputs $In(TS_j)$, and outputs $Out(TS_j)$.

$$TS_j = (s, In(TS_j), Out(TS_j))$$

Definition 4. An abstract service composition SC is $(\{TF_1 \otimes TF_2 \otimes \ldots TF_n\}, \prec f)$, where each TF_l is a composite or atomic service which is associated with a non-functional property NP and represented by an ordered set of operations which has inputs $In(TF_l)$, outputs $Out(TF_l)$, triggered cognition $tCG(TF_l)$ and transactional behavior $bT(TS_l)$.

$$TF_l = (s, NP, In(TF_l), Out(TF_l), tCG(TF_l), bT(TS_l))$$

We choose to realize our system model with a Colored Petri Net formalism (Jensen, 1992). The expressiveness of this formalism has a strong impact on the model quality. A Petri net is represented as a graph with two types of nodes: places and transitions. Places contain data called tokens, and transitions indicate the performed computation. Places are connected to transitions with incoming arcs (i.e., inputs) indicating the tokens that must be consumed, and outgoing arcs (i.e., outputs) indicating the tokens that must be produced in the place. The state of the network is represented by the distribution of tokens over the places. We specifically use hierarchical networks which are an extension of Colored Petri Net formalism to model our cognitive IoT services application. Depending on the nature of the extension, it may be, for example, nodes (i.e., places or transitions) which are substituted by Petri nets or even tokens which are Petri nets. The motivation behind this type of extension is the observation that cognitive-based transactional IoT services need to be manipulated at multiple levels of abstraction where the token which is a Petri net can be dynamically modified. Fig. 5 depicts the cognitive IoT services application modeling using Petri Net formalism. We consider an abstract service composition as a hierarchical petri net where nodes are represented as atomic services displaying the core functionality of a thing (i.e., monitor, actuate, communicate). Cognition composition follows the same representation where nodes consist of cognitive functionalities (i.e, cognitive faculty as per the REASON model). Transaction composition considers recovery actions (e.g., compensation, substitution) as a separate Petri net which can be adapted on-the-fly according to IoT application semantics and execution constraints. According to our model, a cognitive-based transactional IoT application is composed of n Things. A thing's feature is fulfilled by service composition (s_i), augmented by cognition through cognitive services (cs_i) and enriched with transactional behavior by the means of transactional services (ts_i). The data collected and produced by things (d_i) are represented as service's input and service's output.

6. Experiments

We consider the diabetic patient monitoring case study for evaluating the proposed approach. It consists of 16 services built around 6 things that provide sensing, actuating and communicating features. We simulated things by writing several Python programs. The diabetic patient has three implanted objects: GlucoDose, InsulinCheck, and iHealth. In addition to these objects, ambient sensors participate in the IoT system, namely the Accelerometer and the SmartCam.

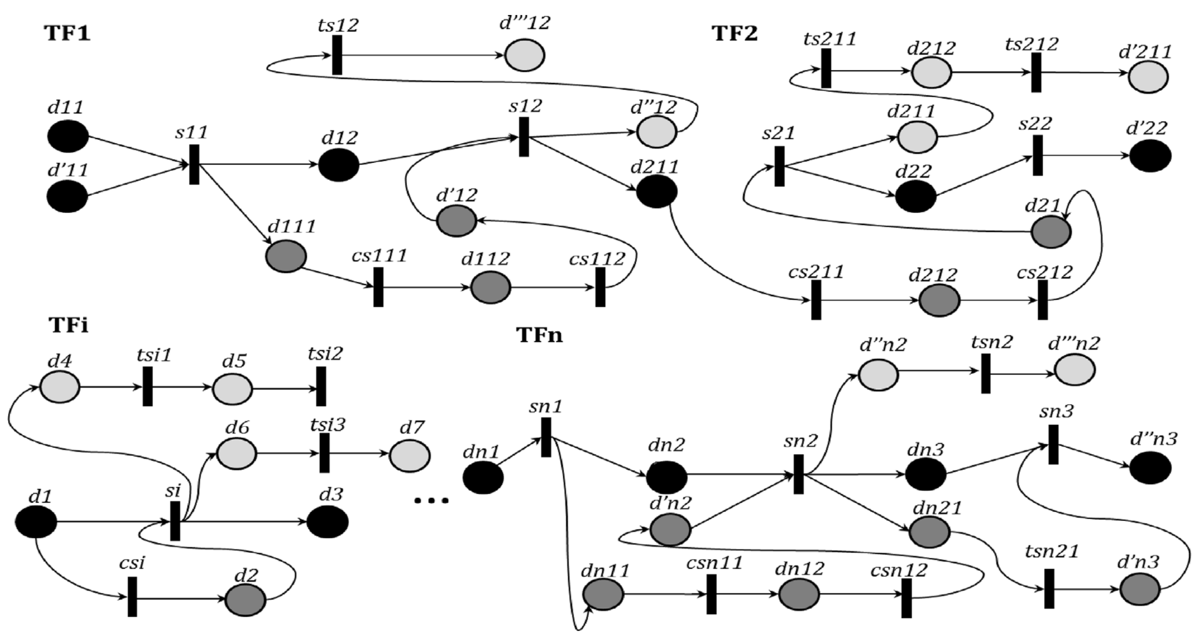

Fig. 5. Succinct illustration of cognitive-based transactional IoT services using Petri Net formalism.

- GlucoDose sensor provides blood sugar measures in mg/dl every 5 min.
- InsulinCheck device collects the provided insulin doses for the last 12 h from the connected insulin pens. Blood sugar variations and insulin administration doses learned at this stage should feed the smartphone reasoning service.
- GlucoDose and InsulinCheck stream data continuously to the patient's smartphone analyzer. It is equipped with an intelligent injector which displays the required insulin dose according to the data analyzer service. When the data analyzer identifies a high or low blood sugar, it sends a message to InsulinCheck injector which actuates the insulin pump.
- Simultaneously, the patient's smartphone keeps interacting with iHealth body sensor within the next 30 min to monitor vital parameters (e.g., pulse rate, respiration rate, blood pressure).
- Ambient sensors materialized by the SmartCam and the Accelerometer stream data and live content to the patient's smartphone in case the injection is not done. The ambient sensors' failure does not affect the system outcome in most cases, thus, they can be switched on and off to reduce resource consumption.
- InsulinCheck injector is locked when all vital parameters are in a normal state and vice-versa. Abnormal situations include hypoglycemia, hyperglycemia and low or high blood sugar levels. The locking/unlocking of the injector depends on both the Smartphone analyzer and GlucoDose data.
- All objects should monitor their resource state to prevent possible failures or inconsistent outcomes (e.g., by enacting self-control cognitive faculty)
- Different recovery mechanisms should be envisaged as per the transactional properties that are tuned according to each core service functionality (Cf. Table 3).

The experiments are conducted on two testing scenarios to evaluate the faultlessness of our model compared to three baseline approaches. The first scenario consists of monitoring a normal patient condition (i.e., 72 to 99 mg/dL) for 8 h at a higher frequency data transfer rate. The second scenario consists of monitoring the patient while presenting 2 hypoglycemia attacks (i.e., below 70 mg/dL) during 12 h at a standard frequency data transfer rate. We considered four empirical studies corresponding to different design levels.

The first baseline approach emulates the behavior of the diabetic patient monitoring system without using cognition and transactional mechanisms. Hence, the cognitive faculties and transactional properties are disabled on this specific simulation. We enable the cognition on the second baseline approach and the transactional properties on the third one. Table 4 depicts the number of services/things involved in each evaluation as per the succinct approach illustration of the self-monitoring IoT application presented in Table 3.

To evaluate the improvement in reliability, the availability metric was recorded for each experiment as follows:

Percentage of availability = (elapsed time − downtime)/ elapsed time

The improvement in adaptability was evaluated using the accuracy metric with respect to data frequency as follows:

Percentage of accuracy = (delivery time − Mean deviation time)/ delivery time

The aim is to calculate the mean deviation time for insulin delivery and the time required for actuating the insulin pump as per the generated data from the different IoT devices throughout the complete data lifecycle. Figs. 6–8 shows the experimental results of all the candidate approaches.

On the other side, the approaches where CF are enabled (Third baseline and our approach) display a greater improvement in accuracy (close to 89%) in comparison to other approaches, which is also an expected result, since cognitive things are augmented with reasoning and learning capabilities that increase the accuracy ratio of insulin administration and delivery time. It is important to note that our approach combines multiple cognitive faculties including self-controlling feature that precludes the possibility to avert potential failures, and hence, assert the self-awareness of participating things. On the contrary, the value of the accuracy metric is much more superior in the first scenario where data are generated at a higher frequency rate, which will help supplying more valuable information to perform accurate predictions at different learning and reasoning stages.

Despite the multitude of the participating services (44 services) and the limitations to manage all these entities together,

Table 4
Overview of the number of things and services involved in each evaluation.

Evaluation candidates	Functional services	Cognitive services	Transactional services	Things
First Baseline	16	None	None	6
Second Baseline	16	15	None	6
Third Baseline	16	None	13	9
Our approach	16	15	13	9

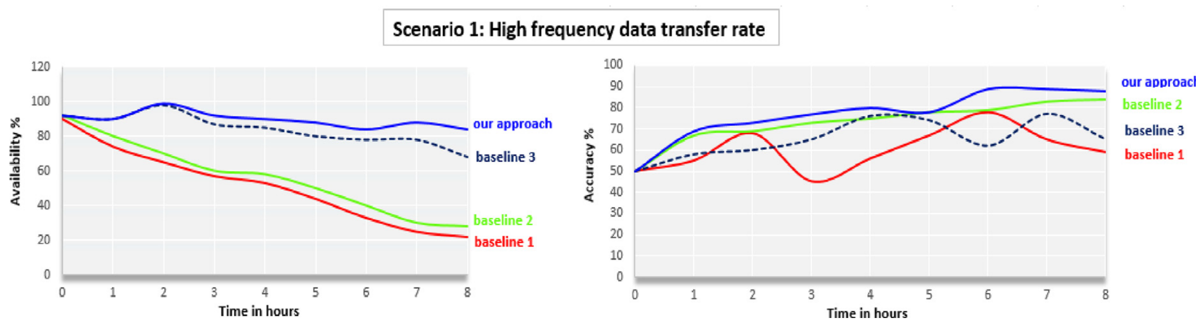

Fig. 6. Availability vs Accuracy as per higher frequency data transfer rate.

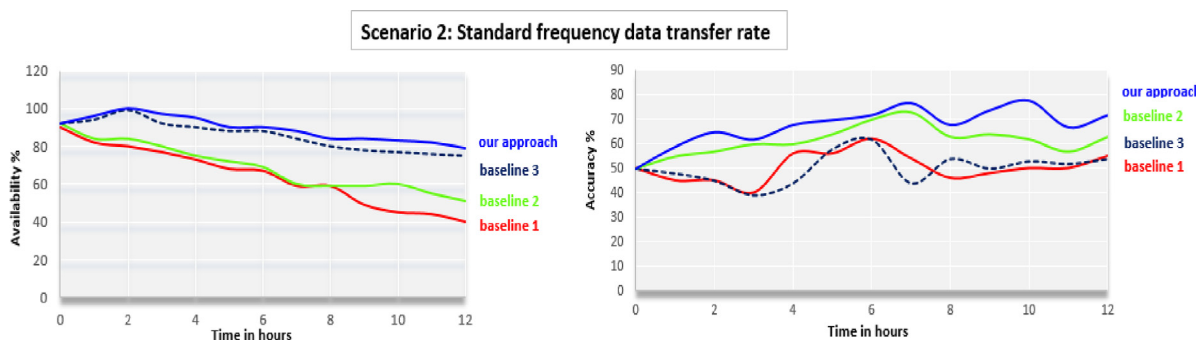

Fig. 7. Availability vs Accuracy as per normal frequency data transfer rate.

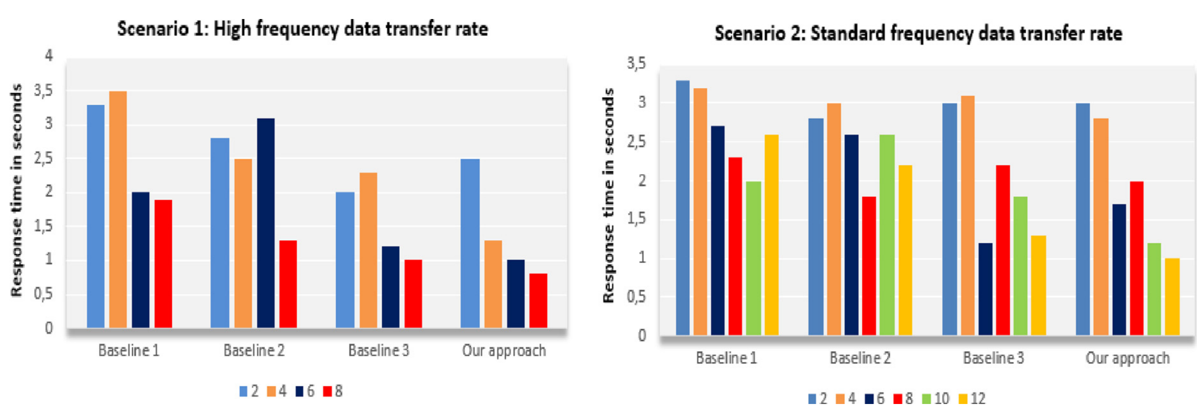

Fig. 8. Response time measure every 2 h vs data transfer frequency.

improvement in both reliability and adaptability was observed to some extent in our approach. The first scenario tested the ideal conditions for normal patient monitoring, in which we could tolerate a mean time deviation and the possibility of switching from failure to acceptable states. The second scenario tested real-world conditions for critical patient monitoring, under which the system should react instantly to 2 hypoglycemia crisis. Our approach exhibits remarkable improvement in response time (0.8 s) compared to baseline approaches particularly in the second scenario where failures are unacceptable. This is due to the flexibility of our model to enable appropriate cognitive faculties, on-the-fly, which improve the data processing time, and to activate the transactional properties in order to perform proactive adaptations, for example, switching-off things that will overload the system (e.g., SmartCam, Accelerometer) or switching to a redundant object (e.g., InsulinCheck).

7. Conclusion

Enhancing reliability and adaptability is substantial to guarantee correct and acceptable outcomes in IoT ecosystem, particularly for mission-critical applications. In this paper, we presented a holistic approach that addresses the problem of both reliability and adaptability issues that affect service execution when handling smart things. The key shift is to add functionalities for cognitive behavior and provide mechanisms that can operate across multiple applications context while fostering self-awareness of things. Thus, we explore the trial of merging transactional properties with cognitive things. We first empower things with cognitive capabilities by introducing the concept of cognitive faculty (CF). Then, we study the appropriateness of enabling a cognitive faculty according to the core functionality of things. Reliability and adaptability are ensured through backward and forward recovery mechanisms. These mechanisms are triggered according to the transactional property of different things. The second step of our approach consists in enabling transactional properties on things. We examine as well the validity of actuating each property on a particular thing. As a result, things are becoming independent entities, which can take smart decisions and perform adaptations according to their cognitive features and their transactional properties. As a proof of concept, as set of experiments have been carried out using a case study in the context of a smart monitoring IoT application for diabetic patients, and further evaluations will be conducted incessantly. The first results of the underlying test bed evaluation indicate how adding a distributed topology evolving multiple service compositions enriched by cognitive features and transactional properties can provide CIoT systems with a greater flexibility. In term of future work, we plan to develop a formal specification to refine the definition of cognitive transactional things. Furthermore, we would like to investigate atomicity, isolation and dependencies as part of CIoT service compositions.

CRediT authorship contribution statement

Widad Ettazi: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft. **Mahmoud Nassar:** Visualization, Investigation, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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