Applying Decisional DNA to Internet of Things: The Concept and Initial Case Study

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Abstract. In this paper, we present a novel approach utilising Decisional DNA to help the Internet of Things capture decisional events and reuse them for decision making in future operations. The Decisional DNA is a domain-independent, standard and flexible knowledge representation structure that allows its domains to acquire, store, and share experiential knowledge and formal decision events in an explicit way. We apply this approach to our current work - SmartBike, a sensor-equipped bicycle built under the concept of Internet of Things. By using Decisional DNA and machine learning algorithms, the SmartBike is able to distinguish its user patterns based upon past riding data. The presented conceptual approach demonstrates how Decisional DNA can be applied to the Internet of Things and bring to them smartness required by incoming semantic networks.

Keywords: The Internet of Things, Decisional DNA, Set of Experience Knowledge Structure, knowledge representation, intelligent systems.

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INTRODUCTION

The Internet of Things (IoT) (Ashton Kevin 2009; Atzori et al. 2010; Tsai et al. 2013) has gained significant attention from industry as well as academia during the past decade. The main reason behind this interest is the capabilities of the IoT for seamlessly integrating classical networks and networked objects (Atzori et al. 2010; Kortuem et al. 2010; Lopez et al. 2009). The motive of IoT is to connect all things in the world to the Internet, and the eventual goal of IoT is to create an intelligent environment around us, where things can function without explicit instructions, communicate with each other, make decisions by themselves, and even know what we want, what we like, and what we need (Tsai et al. 2013; Perera et al. 2009). Moreover, the great progresses on communication, computer, and relevant technologies make many conceptual approaches possible. Therefore, more and more researchers, academics, and governments are taking part in creating such an intelligent environment that is composed of various computing systems, such as smart home, smart health care, global supply chain logistics, intelligent transportation, and social networks just to mention a few (Bandyopadhyay et al. 2011; Danilowicz and Nguyen 2010; Domingo 2012; Duong et al 2000; Miorandi et al. 2012).

Consequently, one of the most critical problems arises: how do we transform the data captured and generated by IoT into knowledge to make our new world a more convenient and intelligent place to live? This is where machine learning and knowledge representation technologies come to play, promising smart solutions for data into knowledge transformation issues. A number of proposals for these solutions can be found in the current literature. In the work of Vlacheas et al. 2013, a cognitive management framework that empowers the Internet of Things to better support sustainable smart city development is presented. The framework introduced the Virtual Object (VO) concept as a dynamic virtual representation of objects and proposed the Composite VO (CVO) concept as a means to automatically aggregate VOs in order to meet users' requirements in a resilient way. In addition, this work illustrates the envisaged role of service-level functionality needed to achieve the necessary compliance between various applications and VOs/CVOs, while hiding complexity from end users. The envisioned cognition at each level and the use of proximity are described in detail, while some of these aspects are instantiated by means of conceptual building blocks. A case study, which presents how the framework could be useful in a smart city scenario that horizontally spans several application domains, is also described. Li et al. (2011) introduced the Smart Community as a new Internet of Things application, which used wireless communications and networking technologies to enable networked smart homes and various useful and promising services in a local community environment. The smart community architecture was defined in their paper, then solutions for robust and secure networking among different homes were described, and two smart community applications, Neighborhood Watch and Pervasive Healthcare, were presented. López et al. (2012) proposed an architecture that integrates fundamental technologies for realizing the IoT into a single platform and examined them. The architecture introduces the use of the Smart Object framework (Vasseur et al. 2010; IPSO 2014) to encapsulate sensor technologies, radio-frequency identification (RFID), object ad-hoc networking, embedded object logic, and Internet-based information infrastructure. They evaluated the architecture against a number of energy-based performance measures, and showed that their work outperforms existing industry standards in metrics such as delivery ratio, network throughput, or routing distance. Finally, a prototype implementation for the real-time monitoring of goods flowing through a supply chain was presented in detail to demonstrate the feasibility and flexibility of the architecture. Key observations showed that the proposed architecture had good performance in terms of scalability, network lifetime, and overhead, as well as producing low latencies in the various processes of the network operation. In another work, Lee et al. (2013) applied human learning principles to user-centred IoT systems. Their work showed that IoT systems could benefit from a process model based on principles derived from the psychology and neuroscience of human behaviour that emulates how humans acquire task knowledge and learn to adapt to changing context.

In this paper, we present a novel approach utilising Decisional DNA to help the Internet of Things capture decisional events and reuse them for decision making enhancement in future operations. The Decisional DNA is a domain-independent, standard and flexible knowledge representation structure that allows its domains to acquire, store, and share experiential knowledge and formal decision events in an explicit way (Sanin and Szczerbicki 2009). We apply this approach to our current work - SmartBike, a sensor-equipped bicycle built under the concept of Internet of Things. By using Decisional DNA and machine learning algorithms, the SmartBike is able to distinguish its user out of other riders based upon its user's past riding data. The presented conceptual approach demonstrates how Decisional DNA can be applied to the Internet of Things and brings them smartness.

SET OF EXPERIENCE KNOWLEDGE STRUCTURE AND DECISIONAL DNA

The Decisional DNA is a novel knowledge representation theory that carries, organizes, and manages experiential knowledge stored in the Set of Experience Knowledge Structure (SOEKS or shortly SOE) (Sanin et al. 2009; Zhang, Sanin & Szczerbicki 2013). The SOEKS has been developed to acquire and store formal decision events in an explicit way (Sanin and Szczerbicki 2009). It is a flexible, standard, and domain-independent knowledge representation structure, as well as a model based upon available and existing knowledge, which must adapt to the decision event it is built from (i.e. it is a dynamic structure that depends on the information provided by a formal decision event) (Sanin et al. 2009); besides, it can be represented in XML (eXtendable Markup Language) or OWL (Ontology Web Language) as an ontology in order to make it transportable and shareable (Sanin and Szczerbicki 2007).

SOEKS consists of variables, functions, constraints and rules associated in a DNA shape permitting the integration of the Decisional DNA of an organization (Sanin et al.

2009). Variables normally implicate representing knowledge using an attribute-value language (i.e. by a vector of variables and values) (Sanin and Szczerbicki 2009), and they are the centre root of the structure and the starting point for the SOEKS development. Functions represent relationships between a set of input variables and a dependent variable; moreover, functions can be applied for reasoning optimal states. Constraints are another way of associations among the variables. They are restrictions of the feasible solutions, limitations of possibilities in a decision event, and factors that restrict the performance of a system. Finally, rules are relationships between a consequence and a condition linked by the statements IF-THEN-ELSE. They are conditional relationships that control the universe of variables (Sanin et al. 2012).

Furthermore, SOEKS is designed similarly to DNA at its essential features: First, the combination of the four components of the SOE gives it uniqueness, just as the combination of four nucleotides of DNA does. Secondly, the elements of SOEKS are connected with each other in order to imitate a gene, and each SOE can be classified, and acts like a gene in DNA (Sanin et al. 2009). As the gene produces phenotypes, the SOE brings values of decisions according to the combined elements. Then a decisional chromosome storing decisional “strategies” for a category is formed by a group of SOE of the same category. Finally, a diverse group of SOE chromosomes comprise what is called the Decisional DNA (Sanin et al. 2012).

In short, SOEKS and Decisional DNA provide an ideal approach which can not only be very easily applied to various IoT domains, but also enable standard knowledge communication and sharing among them (Zhang, Sanin & Szczerbicki 2012).

DECISIONAL DNA-BASED INTERNET OF THINGS

The Decisional DNA-based Internet of Things is designed and developed to enable the IoT for decisional events capturing, and knowledge extracting, reusing and sharing. In order to achieve this goal, the conceptual four-layer architecture is proposed for the Decisional DNA-based IoT, these four layers are: Physical Layer, Operating System Layer, Application Layer, and Decisional DNA Layer (see Fig. 1).

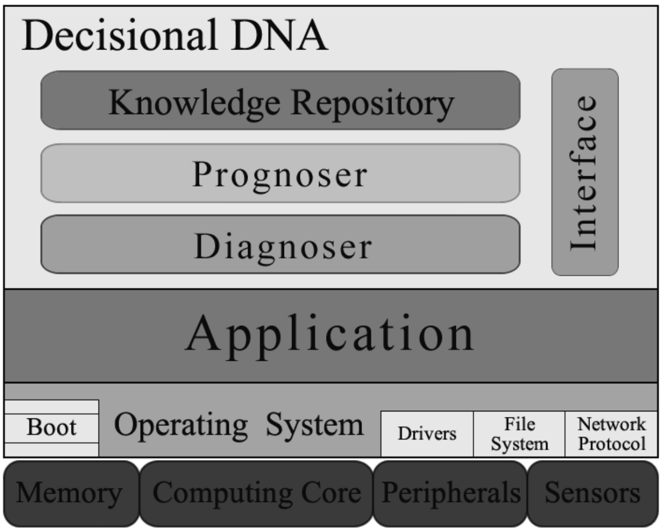

Figure 1. The system architecture for Decisional DNA-based IoT

At the bottom is the physical layer that consists of computing units, networking hardware, memory, peripherals, and most importantly, the sensing entities of IoT. It is the fundamental layer underlying the logical data structures of higher level functions in the system.

At the second level, there is the operating system layer where the operating system of

IoT runs and manages the computing hardware of IoT, and provides data transfer services among the Decisional DNA layer, the application layer, and the underlying physical layer.

Upon the operating system layer, there is the application layer running applications developed to fulfil different tasks and offer various functionalities to the end-user. With the help of the Decisional DNA layer, these applications can access knowledge-based services to make the whole system intelligent and being capable of acquiring, reusing, improving and sharing knowledge.

Finally, the Decisional DNA layer is at the top. It is the core software structure of our proposed structure, and is designed to work as the “brain” in order to bring smartness to IoT applications: it analyses and routes data, learns from data, manages knowledge, cooperates with other mechanisms, and interacts with the IoT application. The Decisional DNA layer is composed of a set of computer software, namely: Interface, Diagnoser, Prognoser, and Knowledge Repository (Fig. 1). The Interface connects the Decisional DNA layer with its outer environment, and provides knowledge-based services and functionalities to the application layer. The Diagnoser is the place where the IoT scenario data is gathered and organized. In our case, we link each experience with a certain scenario describing the circumstance under which the experience was acquired. Scenario data are essential for learning and estimating the status of IoT. The Prognoser is in charge of analyzing scenario data, and creating experiential knowledge based on machine learning and data mining algorithms. The Knowledge Repository is where experiential knowledge stored and managed. It uses XML representation (Sanin et al 2007) which makes standard knowledge sharing and communication easier.

INITIAL CASE STUDY

In order to test our concept, we applied the Decisional DNA to an instance of IoT which is a sensor-equipped bicycle. In this section, we introduce the system architecture, main hardware components, and the initial experiment run on this application.

The Decisional DNA-based bicycle application consists of the sensor-equipped bicycle, a smartphone application (APP), and the Decisional DNA-based IoT platform (see Figure 2).

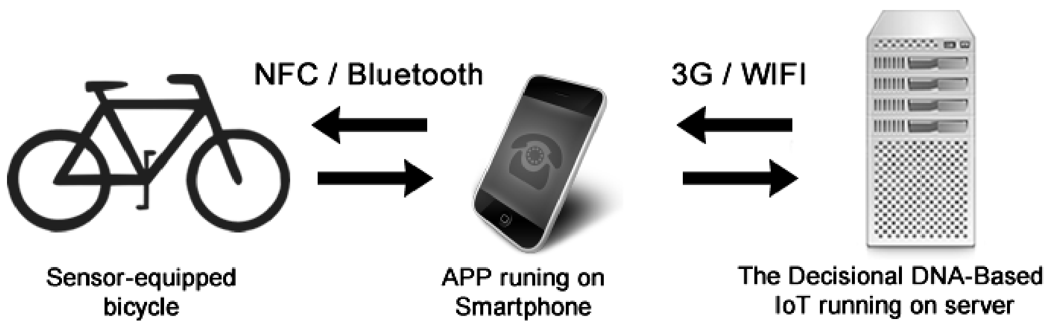

Figure 2. The architecture of Decisional DNA-based bicycle application

On the bicycle part, there are two MD-PS002 pressure sensors installed on a NXP LPC1769 board (NXP 2014) with a HC-06 Bluetooth module. The NXP LPC1769 is an ARM 32-bit Cortex-M3 Microcontroller with MPU, CPU clock up to 120MHz, 64kB RAM, 512kB on-chip Flash ROM with enhanced Flash Memory Accelerator. It supports In-Application Programming (IAP) and In-System Programming (ISP), has eight channel general purpose DMA controller, nested vectored interrupt controller, AHB Matrix, APB, Ethernet 10/100 MAC with RMII interface and dedicated DMA, USB 2.0 full-speed Device controller and Host/OTG controller with DMA, CAN 2.0B with two channels, four UARTs, one with full modem interface, three I2C serial interfaces, three SPI/SSP serial interfaces, I2S interface, General purpose I/O pins, 12-bit ADC with 8 channels, 10-bit DAC, and four 32-bit timers with capture/compare sensors. The NXP LPC1769 board is easy to use, low powered, and very handy to deal with different peripherals and sensors working together.

Through the HC-06 Bluetooth module, the board is able to communicate with the smart phone. By sending commands to the board, the APP running on the smartphone collects data captured from the bicycle. Afterwards, the APP transfers these data to the Decisional DNA IoT platform for further processing. Finally, the Decisional DNA IoT platform sends back processing results to assist the user in operation of the bicycle.

The initial experiment was designed with three aims in mind. First, we examined whether the Decisional DNA can be adapted for the needs of IoT. Second, we tested the capability of knowledge capture by Decisional DNA embedded in IoT. Finally, we checked if the application remembers its users to examine the smartness of our approach.

In terms of the adaptability examination of Decisional DNA, we converted the file format of SOEKS from XML to plain text so that the captured data can be organized and stored on the NXP LPC1769 board. Every minute while user's riding, pressure sensors collected the two tires' real-time tire pressure. Table 1 illustrates a fragment of the tire pressure collected at a given time. The ID is used to indicate two tires: number one stands for the front tire, while number two stands for the rear one. Besides pressure, date and time are captured at the same time as well. They are collected for future use, such as learning the riding routine of the user.

Table 1. A sample of tire pressure data captured

ID	Pressure (bar)	Date	Time
1	1.62	2014-08-03	11:23:51
2	1.53	2014-08-03	11:23:51

By organizing and sending captured data to the APP running on an Android smart phone via Bluetooth connection, tire pressure information was collected, stored, and made ready for post-processing. Finally, we introduced the *FarthestFirst* (Hochbaum and Shmoys 1985) algorithm to learn the user's normal weight distribution based on tire pressure information, and eventually distinguish the current user from other riders (i.e. we performed user clustering). We collect tire pressures when the user is riding in order to train the system, after training, we can change the rider, and the bicycle is able to detect the change from the tire pressure differences. The Fig. 3 shows the result of the user clustering in Weka (Witten and Eibe 2005) by using real-time data of tire pressures - the system clusters the riders correctly. Cluster 1 (marked as a cross) stands for the user, and the other rider is clustered as Cluster 2 (marked as a solid dot).

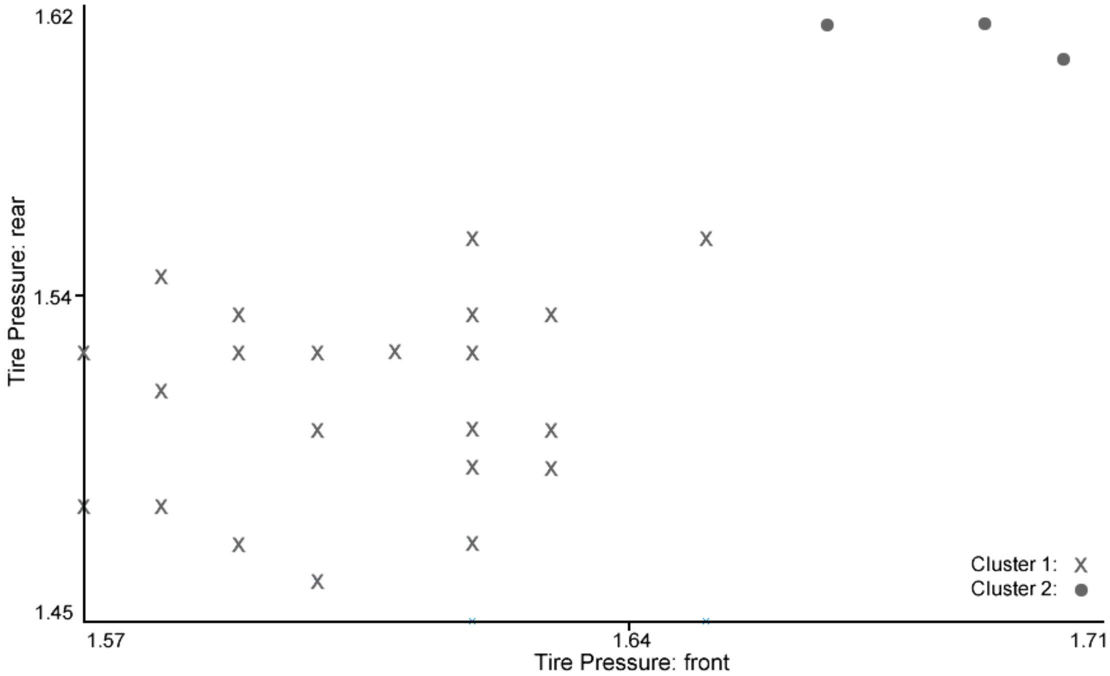

Figure 3. The result of the user clustering.

As we can see from the initial case study, by using the Decisional DNA and some machine learning algorithms (*FarthestFirst* algorithm in this case) we actually enabled implementation of smart IoT application.

CONCLUSIONS AND FUTURE WORK

In this paper, we introduced an initial approach that allows the IoT to capture decisional events, and reuse captured decisional events for decision making in future operations. In this approach, the Decisional DNA is used as the technology of knowledge representation of certain decisional events. Moreover, the adaptability and usability of the Decisional DNA applying to IoT has been tested through an initial case study and experiments.

Making IoT intelligent is a very challenging goal to achieve, and our research is just at the starting point in this new emerging field. We plan to continue with the following improvements and refinements:

- refinement of the requirements of Decisional DNA-based IoT, such as data structure, system design, and life cycle management,
- further development of the Decisional DNA-based IoT platform,
- evaluation and comparison of different knowledge discovery approaches in order to design and optimize knowledge discovery strategy inside the platform, and
- further design and development of open APIs to support connection with a third-party software.

ACKNOWLEDGEMENT

The authors would like to thank the editors and anonymous reviewer for their valuable comments and suggestions on this paper. This work was supported as part of the Project KYTZ201422 by the Scientific Research Foundation of Chengdu University of Information Technology.

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