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From the internet of things to embedded intelligence

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Abstract The Internet of Things (IoT) represents the future technology trend of sensing, computing, and communication. Under the Wisdom Web of Things (W2T) vision, the next-generation Internet will promote harmonious interaction among humans, computers, and things. Current research on IoT is primarily conducted from the perspective of identifying, connecting, and managing objects. In this paper, however, we attempt to enhance the IoT with intelligence and awareness under the W2T vision. By exploring the various interactions between humans and the IoT, we extract the "embedded" intelligence about individual, environment, and society, which can augment existing IoT systems with user, ambient, and social awareness. The characteristics, major applications, research issues, the reference architecture, as well as our ongoing efforts to embedded intelligence are also presented and discussed.

Keywords wisdom web of things · human-IoT Interaction · embedded intelligence · user awareness · ambient awareness · social awareness

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1 Introduction

The Internet of Things (IoT) refers to the emerging trend of augmenting physical objects and devices with sensing, computing, and communication capabilities, connecting them to form a network and making use of the collective effect of the networked objects. Earlier networked objects include surveillance cameras mounted in the city environments and sensor-equipped everyday artifacts (e.g., goods with RFID tags) in diverse smart spaces. The emerging categories of IoT devices tend to be mobile, which include wearable sensors (e.g., pedometers, biosensors), sensor-enhanced mobile phones (e.g., the iPhone), and smart vehicles (vehicles equipped with sensing devices, such as GPS devices).

Several emerging technologies have contributed to the proliferation of IoT in recent years. Radio Frequency Identification (RFID), Near Field Communication (NFC) and Wireless Sensor and Actuator Networks (WSAN) have developed as atomic components of IoT, enabling auto-identification and interconnection of objects [3, 39, 42]. Service-oriented computing [7, 11] and the Semantic Web [32, 38] technologies facilitate the development of applications and sharing of legacy information. They work at the middle-ware layer of IoT systems to hide the details of different technologies in IoT infrastructures. Cloud computing enables developers to offload services to backend servers, providing unprecedented scale and additional resources for computing over large-scale sensor data obtained from widely deployed IoT devices [54, 55]. The Web of Things (WoT) integrate Web and sensing technologies together by reusing existing Web standards (e.g., URI, HTTP, REST) so as to extend the eco-system of smart objects and enrich the contents provided to users [24].

So far the main research efforts on IoT have been conducted primarily from the perspective of managing objects and resources, ranging from object identification/networking, data access, to object control. This paper, however, attempts to enhance the IoT from the perspective of extracting intelligence and knowledge leveraging the interaction of human and objects. Instead of focusing on connecting and managing smart objects, we emphasize on bringing awareness and enhancing intelligence to the IoT system by analyzing the interactions between humans and smart objects (e.g., passing by street cameras, carrying mobile phones, and commuting in smart vehicles). In [61], Zhong et al. propose the Wisdom Web of Things (W2T) vision, which represents a holistic intelligence methodology for realizing harmonious interaction among humans, computers, and things in the hyper world. The hyper world is a combination of the social world, the physical world, and the cyber world. Our work is under this pioneering vision, and particularly studies the harmonious interaction between human and IoT devices in the coming hyper world. To implement the W2T vision, W2T further presents the "*things-data-knowledge-services-human-things*" data cycle. Our study focuses on human-IoT interaction data processing, majorly falling into the "*data to knowledge/intelligence*" transformation stage in the W2T data cycle. We investigate different ways of human-IoT interaction, and explore different kinds of knowledge and intelligence that can be extracted from the historical interaction data.

More specifically, we aims to study how the IoT reveals high-level knowledge about *individuals* (e.g., user A's preferences), *groups of people* (e.g., the relationship between users A and B), and *society* (e.g., hotspots or areas of unrest in a city) by analyzing the digital traces (e.g., video captured, call logs, GPS trajectories) left by people while interacting with the IoT. High-level knowledge cannot be obtained directly from IoT devices; instead, it is derived indirectly from raw sensing data using advanced data mining and machine learning techniques. We call the knowledge learned from human-IoT interaction "embedded intelligence (EI)," which refers to *the knowledge about human life, ambient dynamics, and social* *connection/interaction*. A considerable variety of innovative applications can be enabled by EI-enhanced IoT, in areas such as real-world search, social networking, enterprise management, community sensing, intelligent transportation, and so on. We use a simple scenario to illustrate concrete ideas about EI in the IoT.

The scenario places itself in the context of an urban environment. Chen is a university student in Beijing. He lives a little far from the campus and usually travels to the university by bike or public transportation. The mobile phone has become his personal companion, enabling him to connect with his friends anytime, anywhere. Taking advantage of the capability of existing IoT (or **pre-EI**) systems, we can determine where Chen is, who he has encountered, and where the next bus is. All this information can be retrieved from sensor readings in GPS and Bluetooth logs. By analyzing the collected digital traces to extract EI from the IoT (i.e., in the **post-EI** era), however, we can infer high-level knowledge about Chen and the community. His activity (e.g., walking on the street), his interests (e.g., points of interest learned from his location trails), his relationship with others (predicting which encounter may be his friend), and the traffic dynamics in the city (e.g., detecting hotspots and traffic jams in Beijing using citywide vehicle and mobile phone data), among others, can be deduced. Advanced human-centric services can be enabled using the derived EI information, such as traffic planning and friend recommendation.

There are several closely related research areas that are interleaving with EI, i.e., ubiquitous intelligence [37], brain informatics [58, 62], Web intelligence [59, 60], social computing [52], and reality mining [16, 17]. Compared to EI, ubiquitous intelligence highlights the context-awareness feature of individual objects, it does not target at the study of aggregated intelligence (e.g., social interaction patterns) from large-scale objects. Brain informatics also studies human behaviours, leveraging various powerful techniques, such as fMRI, eye tracking, and EEG [62]. EI, however, aims to understand human behaviours from their daily interaction with smart objects. Both Web intelligence and social computing devote to Web data understanding, but the latter one focuses on the analysis of human interaction and social behaviours from social websites. Comparing with them, EI addresses the understanding of human behaviours in the physical world. While reality mining studies the relationship between people, EI extends its scope from social tie measurement to individual and urban sensing. Further, instead of using merely mobile phones for reality mining, EI aggregates the information from various IoT devices, including static infrastructure, mobile phones, vehicles, and so on. This paper attempts to depict a picture about EI under the W2T vision. More specifically, it aims to:

- present the categories of IoT devices that EI is embedded into and the characteristics of EI;
- illustrate the major benefits of EI in everyday life and analyze the major research challenges faced by the scientific community;
- propose a reference architecture about how to derive EI in IoT systems and describe our ongoing practice to EI.

Our work on EI is particularly useful to understand the importance of information processing and intelligence extraction in the W2T data cycle. The definition and usage of EI is human-centric, demonstrating the harmonious-interaction view over human, computers, and things in W2T. We also study how the extracted knowledge and intelligence of EI can bring to the existing IoT systems in terms of awareness, and how they will nurture novel W2T applications.

2 Embedded intelligence: a research overview

The terminology "embedded intelligence" is not new. It was used early by Schoitsch et al. in 2006 [48], where embedded intelligence is characterized to span the gap between sensor networks and applications in smart environments (e.g., autonomous systems, assistant living systems, personal robots). The term also appeared in Jedermann et al.'s work [29], by exploring the advantages of introducing RFID-enhanced objects in logistics. Comparing with them, the "meaning" of embedded intelligence (EI) is refined and extended from two aspects in our work: (1) EI is a human-centric concept, aiming to understand human behaviours from their daily interaction with smart objects; (2) with the prevalence of mobile and wearable devices, the scope of EI goes beyond individual smart environments to large-scale community and urban environments, and many novel applications are enabled (e.g., urban planning, community sensing).

Research on extracting EI (i.e., harvesting knowledge about human behaviors, ambient dynamics, and social interaction) from the digital traces of human-IoT interaction is still in its infancy. Although there is still not a clear definition that addresses this research direction in the IoT community, the initial form of EI has already been explored in several categories of IoT devices. This section presents an overview of related research on EI as explored in six typical sources, with each source corresponding to a traditional or emerging category of IoT device.

2.1 Surveillance cameras

A surveillance camera forms part of a static sensing infrastructure, which is an early type of static sensor that is widely deployed in urban environments (e.g., public or critical spots in the city). We use the surveillance camera as an example to illustrate how a network of static sensors can sense human activity or interaction.

Ongoing human activities within an area can be determined by analyzing the scenes captured by a fixed surveillance camera at a certain location. For example, Saxena et al. [47] developed a video-based system that recognizes crowd behaviors (e.g., fighting, street passing) in public places. By analyzing interpersonal interaction patterns, researchers have also studied the social relationship among co-located people. For example, Ding and Yilmaz [14] determined how to identify groups and distinguish the leaders of each group from video sequences. The authors used two statistical learning methods to derive the affinity between individuals.

The combined power of surveillance cameras widely deployed and networked in a city can help solve a series of social challenges, such as traffic forecasting and public safety protection. For instance, Memphis in the US uses the CRUSH system, developed by IBM, to monitor the hotspots around the city and predict crimes (http://www.memphispolice.org/). CRUSH works using a series of crime patterns learned from historical crimes and arrest data, in combination with other factors such as weather forecasts, economic indicators, and information on events, such as paydays and concerts.

2.2 Smart indoor artefacts

With the development of wireless sensing techniques, widely available inexpensive and tiny sensors (e.g., RFID tags) are deployed to enhance the performance of everyday objects (i.e., smart artifacts [49], such as smart tables, smart cups, etc.) in daily living environments. Because many of our daily activities involve interaction with everyday objects, human activity becomes an important high-level context that can be learned from human-artifact interaction. When only one smart artifact is used, we can detect simple activities relevant to that object. For instance, in the MediaCup project [6], cup-specific human activities, such as *drinking* and *water adding*, can be recognized by interpreting the data from a sensor-equipped cup. By contrast, when a collection of smart artifacts is deployed in a smart environment, more complex human activities can be detected by referring to interactions with a series of objects. For example, Philipose et al. [45] have explored HMM techniques to recognize tens of household activities (such as preparing food, washing clothes, etc.) by analyzing people's use-trails of a number of RFID-equipped indoor objects. The mined human activity information is beneficial to society, especially in the healthcare and eldercare domains. However, smart-artifact based activity recognition is restricted to closed-instrumented environments [28].

2.3 Wearable sensors

The defect of indoor smart artifacts is remedied with the presence of wearable sensors (e.g., accelerometers, pedometers, microphones). Wearable sensors are worn on different parts of the human body to enable human-centric sensing anytime, anywhere. The sensors extract a number of high-level contexts, such as human activity, daily routines, and social situations, about sensor wearers. Bao et al. [5] developed classifiers for detecting physical activities (e.g., sitting still, standing, walking), which are detected from the data acquired by five small accelerometers worn on different parts of the body. Instead of using classifiers to recognize a predefined set of activities, some researchers have attempted to find unknown activity patterns (i.e., discovery of routines) without any predefined models or assumptions. For instance, in [28], a topic model-based approach is proposed to identify daily routines, such as shopping or commuting, from the raw sensing data collected by body-worn accelerometers. Wearable sensors that detect the social situations of users (e.g., having a meeting, having coffee with friends) have also been explored [30].

2.4 Mobile phones

Although wearable sensors are portable and promising, they are still not widely used as "personal companions" in daily life. Things change with the proliferation of sensor-enhanced mobile phones, in which a number of sensors, such as GPS receivers, Bluetooth/Wi-Fi, accelerometers, ambient light, and cameras, are embedded. With these sensors, phones can track movements (of users) in the physical world, monitor preferences, track Internet content consumption, and so on. The huge volume of multi-modal data collected from the daily use of smart phones provides unprecedented opportunities to study individual/social contexts and ambient dynamics.

- *Human activity*. As one particular type of wearable/portable device, a mobile phone sensing system can easily be incorporated with a human activity recognition method, as demonstrated by the CenceMe application on the iPhone [10].
- *Space semantics*. Locating a person in the physical world using GPS-equipped mobile phones is easy. However, a GPS does not work indoors. Instead of deploying cumbersome sensing infrastructure (e.g., ultrasonic sensors [27], RFID tags [56]) to enable indoor positioning, researchers have investigated a simple mobile phone-based method to identify in which type of space a user is located. For example, SurroundSense uses a combination of sensed ambient light, sound, and video data from mobile phones to predict the semantics (e.g., bookstore, restaurant) of user location [4].

- *Social relationships*. By logging various aspects of physical interactions and communication among people (e.g., co-location, conversations, call logs) and mining user behavioral patterns (e.g., places of interest), mobile phones can be used to analyze and predict social relationships among people. For example, the Reality Mining project of MIT can infer 95 % of friendships on the basis of observational data from mobile phones [17].
- *Human mobility patterns*. Observing and modeling human movement in urban environments are essential for the planning and management of urban facilities and services. However, a key difficulty confronting urban planners and social scientists includes the challenge and cost of obtaining large-scale and real-world observational data on human movement. The massive volume of sensing data collected from mobile phones, however, paves the way for studying large-scale human movement patterns (e.g., where people often go at 9:00 pm in Tokyo). For example, an interesting study based on the monitoring of 100,000 mobile phone users, conducted by Northeastern University in US, revealed that human movement has a high degree of spatio-temporal regularity [21].
- *Ambient contexts*. The nomadic and in-situ nature of mobile phone sensing provides a new opportunity for ambient context sensing (e.g., air quality level of a street). For example, the BikeNet application measures several metrics to provide a holistic picture of cyclist experience, including the CO_2 level along a bike path [18].

2.5 Smart vehicles and smart cards

Along with the rapid development of mobile phone sensing systems, the prevalence of sensor-enhanced vehicles (e.g., GPS) and smart cards used in public transportation systems opens another window for understanding the pulse of a city. Liu et al. [35] reported the use of multiple real-time data sources (GPS data from taxis and smart card data from buses) to understand daily urban mobility patterns and traffic dynamics (e.g., hotspot detection). Morency et al. [41] investigated the spatio-temporal dynamics (e.g., examining the effects of weather on transit demand) of public transit networks, leveraging the 10 month bus boarding records collected from a city in Canada.

3 Characterization of embedded intelligence

Each of the above-mentioned sensing sources has strengths and limitations in capturing the full spectrum of EI. To exploit the rich intelligence embedded in the IoT and support diverse applications, heterogeneous sensing sources with different capabilities should be aggregated to extract the distinct dimensions of EI. This section begins with a characterization of diverse IoT sources in terms of sensing style and coverage. We then present three different interaction schemes between humans and the IoT. We also elaborate on how these interaction schemes lead to the three dimensions of EI.

3.1 Diversity on sensing style and coverage

In terms of the relationship between IoT devices and human community, we identify two distinct styles of smart object sensing (Figure 1).

– *Object-centric (third-person) style*. Smart objects belonging to this type are deployed in the real world. They can detect the changes in their physical status as well as changes in the surrounding environment. This sensing style does not link a sensing device to a

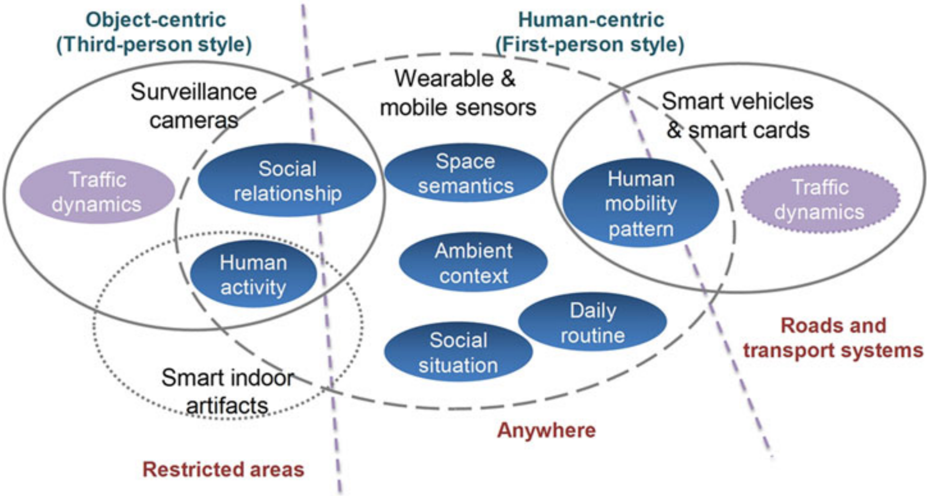


Figure 1 Diversity in sensing style and coverage of distinct IoT devices.

particular person; the device observes the world changes within its range of perception like third-person observers. Surveillance cameras and smart indoor artifacts belong to this type.

– *Human-centric (first-person) style*. Smart objects belonging to this type serve as personal companions (e.g., worn on or attached to the human body, carrying human when they travel). Its placement or location in relation to the user enables the object to share the first-person perspective of the user, and continuously senses user contexts, such as his/her physical activities, daily encounters, and location trails, as well as the situation in which he is immersed. All the other types of IoT devices presented in Section 2, such as wearable sensors, mobile phones, smart vehicles, and smart cards, belong to this category.

In addition to sensing style diversity, heterogeneous sensing sources also differ from one another in terms of coverage capability. The word "coverage" has two meanings: *geographical coverage* (*geo-coverage*) and *logical coverage*.

– *Geo-coverage* pertains to the area covered by a sensing device. Object-centric sensing devices are usually restricted to specific areas. For example, surveillance cameras are installed in a critical spot for small-area monitoring. Human-centric devices break through coverage boundaries by extending the coverage to the scale of a town or city. For example, vehicles and smart cards can predict human mobility patterns in an urban area.
– *Logical coverage*, in simple terms, stitches together geo-coverage observations along multiple abstract dimensions: spatial, temporal, social, and so on. Figure 1 shows that although diverse categories of IoT devices have shared features, they also possess distinct strengths with respect to the logical/semantic data (e.g., human activities, space semantics) that can be learned from them (detailed in Section 2). Wearable and mobile sensors have the largest logical coverage among the referred sensing sources.

3.2 Three dimensions of embedded intelligence

Various IoT devices are weaved deeply into the fabric of everyday life. The diverse features of these devices present unprecedented opportunities to understand the aspects of interaction between humans and real-world entities. We characterize these interactions as *human-object*, *human-environment*, and *human-human* interactions. These interaction patterns can be further elaborated into the three distinct dimensions of EI, namely, *user awareness*, *ambient awareness*, and *social awareness* (as illustrated in Figure 2). We characterize the attributes of the three dimensions as follows.

- *User awareness* refers to the ability to understand personal contexts and behavioral patterns. Examples include human location, human activity, and daily routine patterns.
- *Ambient awareness* concerns status information on a particular space, which ranges from a small space to a citywide area. Examples include space semantics (i.e., the logical type of a place, such as a restaurant), ambient contexts, and traffic dynamics (e.g., traffic jams, hotspots).
- *Social awareness* goes beyond personal contexts and extends to group and community levels. The objective is to reveal the patterns of social interaction (e.g., group detection, friendship prediction, situation reasoning), human mobility, etc.

The three dimensions of EI function at distinct scales. At the micro-scale, the aggregated power of the dimensions improves the quality of human life by anticipating user needs and environmental changes. At the macro-scale, these dimensions provide real time decision support for crowds, social scientists, and urban managers. As a new research area, the semantic data (high-level contexts, patterns, etc.) covered by the three EI dimensions are expected to expand (going far beyond the eight types summarized in Figure 1) in the coming years.

In W2T, harmonious symbiosis among humans, computers, and things in the hyper world is the major concern. Our work is under the W2T vision, and from the view of W2T data

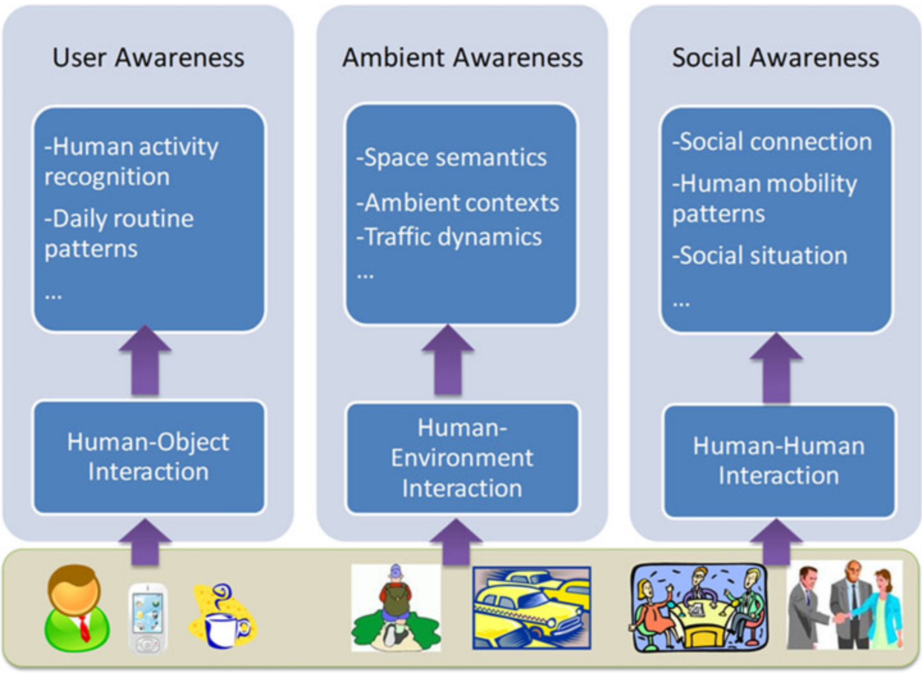


Figure 2 Three dimensions of EI.

cycle, EI fits into the "*data to knowledge/intelligence*" transformation stage. In W2T, "data" is considered as the bridge to connect cyber, social and physical worlds. Data is also crucial for EI, where the hidden intelligence are mined from the "data" collected in human-IoT interactions. EI can be viewed as a significant research direction under the W2T framework, with the aim of exploring the characteristics, technologies, and potential challenges of intelligence extraction from large-scale human-IoT interaction, to enable novel and intelligent W2T applications. In the following sections, we will further present the EI enabled application areas as well as the challenges faced by it.

4 Application areas

In addition to traditional IoT application areas, such as transportation and logistics, healthcare, and smart environments, among others, EI has the potential to significantly enhance IoT systems, at least in the following application domains.

4.1 Real-world search

The increasing number of embedded sensor nodes connected to the Internet enables the observation of an ever-increasing proportion of real-world entities (i.e., people, places, events) via a standard Web browser. Previous studies have focused on searching the location of entities in small-scale and indoor environments. For instance, a search system called MAX was built for human-centric, on-demand searching and location of physical items with the RFID tags [56] in smart homes.

Real-world search is now moving from merely location reporting to high-level human context extraction and retrieval. As envisioned by Google researchers in Nature magazine [43], search contents in the future will cover histories of social interactions with colleagues or friends, and track city hotspots from GPS devices. Google initiated this practice with its real-time traffic condition service [22]. Sense Networks Inc. (http://www.sensenetworks.com/) has also conducted interesting work. Citysense [44], a mobile application developed by this company, supports real-time discovery of hotspots in urban areas.

4.2 Lifelogging

Human memory is fallible. Most people often find the details around what they have done and what they have to do difficult to recall. The failure to remember is a serious inconvenience and negatively influences well-being and performance in the workplace. With the advent of wearable and mobile devices in recent years, numerous digital lifelogging systems that aim to augment human memory through suitable means to capture, store, and access daily experiences (e.g., meeting friends on the road, having lunch in a restaurant) have been developed. Microsoft's MyLifeBits [20] is a pioneering lifelogging project, dedicated to capturing the complete human experience through a wearable camera and an audio recorder. Cyber-I [36] aims to build a counterpart of each person in the cyber world that can intelligently process individual experience data and help people in need. The complete capture of people's lives can bring much noisy data that may never be retrieved, thereby increasing user effort in data retrieval. Thus, lifelogging system designers now focus on the capture of selected scenes that are important to users. For example, the Social Contact Manager (SCM) that our group developed is a scene-specific lifelogging system [26]. It can capture the social interaction contexts (using mobile phones) between a person and his/her contacts, and support associative retrieval of the contacts in name-slipping situations using auto-gathered contextual cues (e.g., when/where/with whom was the contact met).

4.3 Mobile social networking

Forging social connections with others is the core of what makes us human. Mobile social networking (MSN) aims to improve social connectivity in physical communities by leveraging the information detected by mobile devices. Social Serendipity is one of the earliest MSN studies, in which matching interests among nearby people who do not know one another are indicated as a cue for informal, face-to-face interactions [15]. The CenceMe project exploits off-the-shelf smart phones to automatically infer human activity (e.g., walking on the street, dancing at a party with friends), and then shares this information through social network portals (e.g., Facebook) [10]. Li et al. [34] proposed a friend recommendation approach that mines similarities among users (e.g., points of interest) on the basis of their location histories, collected from GPS-equipped mobile phones.

4.4 Enterprise computing

Deploying and using smart objects in enterprises facilitate communication and collaboration among co-located or non-co-located employees. The use of smart objects can help us understand organizational and societal behaviors in enterprises. For example, the SixthSense project of Microsoft [46] uses RFID-tagged objects/devices to infer a range of enterprise intelligence, such as the interaction and association between people and workplaces. The collected data are then used for enterprise services, such as automatic bookings of conference rooms. Ara et al. [2] used specially designed work badges to study the relationship between productivity and interpersonal interactions in a workplace.

4.5 Urban planning

Understanding human movement in urban environments has direct implications for the design of public transport systems (e.g., more precise bus scheduling, improved services for public transport users), traffic forecasting (e.g., hotspot prediction), and route recommendation (e.g., for transit-oriented urban development). A number of studies have extracted citywide human mobility patterns using large-scale data from smart vehicles and mobile phones. The Real Time Rome project of MIT uses aggregated data from buses and taxies to better understand urban dynamics in real-time [9]. Liu et al. [35] reported that the spatio-temporal patterns of taxi trips are essential for a more refined urban taxi system, which enables the control of taxi supply according to travel demands in space and time.

4.6 Community sensing

Community sensing [31] pertains to the monitoring of large-scale phenomena (e.g., air pollution map of a city) that cannot easily be measured by a single individual, but by the active involvement of many citizens (during their daily commutes in the city). Community sensing leverages the mobile nature of humans and the existing or emerging sensing capabilities of mobile/wearable devices, such as sound sensors, air quality sensors, and so on. For instance, the MIT Owl project [50] takes advantage of the network of smart phones equipped with GPSs, compasses, and directional microphones to assess owl populations in a huge region. By sensing the CO_2 and noise levels along a cycling path, the Bikenet application enables multiple users to share and merge individually collected data to create the pollution and noise maps of their city [18]. By analyzing the large number of geo-tagged Twitter messages posted from GPS-equipped mobile devices, Lee et al. has proposed a method to detect unusually crowded places (e.g., a fireworks festival in a park) [33].

5 Key challenges and concerns

Developing the potential benefits offered by EI poses a number of challenges and concerns, many of which are motivated directly by the applications discussed earlier. In facilitating the development of EI in IoT systems, a fundamental issue is the collection and management of multi-modal data from different data sources. Other important issues include better use of classifiers in terms of complex sensing contexts, as well as the privacy and economic concerns raised by the detection and sharing of human daily experiences.

5.1 Sensing with human participation

EI can task deployed mobile sensing nodes (e.g., wearable/mobile devices, vehicles) to contribute data for community use (i.e., community sensing in Section 4.6; real-world search and urban planning applications also explore community sensing data). Compared with traditional static, centrally controlled sensor networks, the involvement of mobile human volunteers in gathering, analyzing, and sharing local knowledge in an interactive sensing infrastructure raises new issues.

Human roles The roles people play in community sensing need clarification. An example is whether they should be interrupted to control the status (e.g., acceptance, execution) of a sensing task. Previous studies have proposed two different views. The *participatory view* explicitly incorporates people into the task processing stage (e.g., deciding which application request to accept, capturing and interpreting the data required) [8]. Conversely, the *opportunistic view* shifts the burden of users by automatically determining when the devices can be used to satisfy application requests [10]. There are limitations to the two perspectives. Purely participatory sensing places many demands on involved users, whereas the opportunistic approach, although more autonomous, suffers from issues such as potential leak of sensitive personal information and high computation costs incurred from decision making (e.g., deciding whether the sampling condition is satisfied). Future work should involve balancing the control load of users and computation load of mobile sensing nodes. Similar to Ganti et al. [19], we envision future community sensing to span a wide spectrum of user involvement, with participatory and opportunistic sensing at the two ends. The proportion of human involvement, however, will depend on application requirements and device/network capabilities.

Sensing task assignment and data sampling In community sensing, using mobile sensors from a highly volatile swarm of sensing nodes can potentially provide coverage where no static sensing infrastructure is available. Nevertheless, because of a potentially large population of mobile nodes, a sensing task must identify which node(s) may accept a task. A set of criteria should be considered in filtering irrelevant nodes: the specification of a required region (e.g., a particular street) and time window, acceptance conditions (for a traffic-condition capture task, only the phones out of user pockets and with good illumination conditions can satisfy requirements), and termination conditions (e.g., sampling period).

Some preliminary studies on these issues have already been initiated. For example, in [12], a task description language called AnonyTL was proposed to specify the sample context for a sensing task. However, improving the efficiency of the decision making process in task assignment and data sampling necessitates further efforts.

5.2 Data collection and representation

As in EI-enhanced IoT systems, data producers can be very different in terms of modality (static or mobile), resource capabilities, data quality (high or low), and sharing willingness. Data consumers are also heterogeneous in terms of running environments (applications that run locally or at community level remotely) and data needs (some need only high-level context information, while others need raw sensor data). Heterogeneity brings forth several challenges for data collection and management.

Architecture for data collection: centralized or self-supported IoT systems use heterogeneous sensors, in which some sensors may not have computing or storage resources while others have relatively better functionalities. This situation gives rise to two distinct data collection methods: The *centralized* method transports all sensor data to a resource-rich backend server to perform data processing, whereas the *self-supported* method endows the device itself with the ability of data processing. The Maui project [13] uses the centralized method, which advocates the use of clouds for performing all data processing tasks while building only a thin layer on the phone itself. The activity recognition tasks of CenceMe [10], are performed on the phone (i.e., the self-supported method). Both approaches have benefits as well as drawbacks, and present specific challenges and opportunities. For example, the data from a group of users collected via the centralized approach offers opportunities for group behavior or large-area dynamics extraction, but the cost associated with the transport of sensor data is high. Although the *self-supported* approach presents the advantage of providing more scalable solutions, it may affect the execution of other applications in the device because of resource limitations. Future work should consider a hybrid plan that considers the trade-off between the cost for on-the-phone computation and that for wireless communication with backend servers.

Standards for communication and knowledge representation Leveraging the sum of data from widely deployed sensors is a key enabler of EI. However, accessing data from distinct IoT devices can be a technical challenge. Sensors come from different platforms vary in bandwidth capabilities, connectivity to the Internet (e.g., constant, intermittent, or affected by a firewall), and connection methods (3G, WiMax, etc.); the sensors might have different access interfaces. To hide much of this complexity, there should better be a standard approach that can provide a uniform interface for collecting, sharing, and querying sensory data from IoT devices. Some efforts are ongoing. For example, the OGC Sensor Web Enablement (SWE) [51] is devoted to building a unique framework of open standards (e.g., XML, Web Service, IEEE 1451) for exploiting Internet-connected sensors of all types. Similarly, the SenseWeb project [23] of Microsoft presents an infrastructure for shared sensing using standardized web service APIs. The unified method for representing the high-level contexts extracted from raw sensing data is another important factor. A shared semantic framework should be introduced to facilitate EI representation and retrieval, as demonstrated in ontology-based studies [25, 53].

5.3 Uncertainty handling

The sensed data from IoT systems have many sources of uncertainty, which may influence the accuracy of subsequent data processing. For instance, embedded sensors can be broken or may report error data, and the sensing environment may generate a considerable volume of noisy data. Taking RFID-based human activity recognition for example [45], if several RFID-equipped objects are placed close to each other, the RFID-reader worn on the human body can detect them simultaneously, consequently affecting the final recognition result. Although the detection and recovery aspects of faults or failures in challenging environments are critical to many IoT applications, little research has been done on these issues.

The involvement of human participation in community sensing also brings forth certain uncertainties to EI extraction. For example, anonymous participants may send incorrect or even fake data to a data center. The lack of control over ensuring source validity and information accuracy can lead to data credibility issues. Therefore, trust maintenance and abnormal detection methods should be developed to determine the trustworthiness and quality of collected data.

5.4 Learning complexity and model selection

Understanding the individual and group behaviors in gathered IoT data necessitates the exploration of a set of classifiers. However, many real-world issues arise when data processing task takes place out of controlled lab settings and is governed by uncontrolled users.

Lack of a common model Humans behave in idiosyncratic ways under a variety of unstructured environments. It is therefore difficult to train a generic classification model that works well in different contexts. For example, a person can walk with his/her mobile phone in hand or in his/her pocket, which may affect recognition accuracy when a common activity recognition model is used. In this context, training different classifiers that work in varied contexts (or even work for different users) is a more efficient approach. However, learning from data requires labeling; given the large number of behaviors to be recognized, the diverse contexts to be considered, and the fact that end users are lay persons, it is impractical to expect much labeled data. The importation of mature semi-supervised or evolvable learning techniques is a promising solution to this problem (we call it the sparse data labeling problem). Leveraging user collaboration/sharing in the data labeling process also hold promise for reducing training time and labeling effort, as demonstrated in [40].

Complexity and ambiguity The accurate extraction of EI information is challenging because of the complexity of daily settings. Successful research on human activity recognition, for example, has thus far focused on recognizing simple individual/group activities in lab environments. Many new challenges, however, emerge in uncontrolled environments. First, people can engage in several activities simultaneously in the same place. For example, a person can answer a phone call while walking with a friend along a street. Little effort has been devoted to recognizing such concurrent activities. Second, similar situations or even the exact one can be interpreted differently. Various interpretations lead to ambiguity and system inconsistency. For example, “picking up the wallet” can be classified under several activities, such as “leaving home” and “cleaning.” A group of co-located phones can compute different inference results about a social situation, such as “in a party” or “in a meeting,” because of slight environmental differences.

Other than the issues raised by the complex nature of individual or group activities, understanding and predicting human behavior and interaction at the community level can be facilitated by the findings of recent social science and physical studies. For example, patterns such as power-law/small world topology have been found in networks that range from friendships in school to co-authorship networks in the sciences [1, 42]. Other techniques and models about large-scale network systems should also be exploited in future EI research, such as random graph theory, scale-free networks, and so on.

5.5 Privacy concerns

The sharing of personal data in applications (e.g., contributing data to community services, such as citywide pollution monitoring) can raise significant privacy concerns, with information (e.g., location, point of interests) being sensitive and vulnerable to privacy attacks. The new security challenge introduced here is the *protection of the privacy of participants while allowing their devices to reliably contribute data to community-scale applications*. Some researchers have focused on using data anonymization techniques to conceal the identity of users when they contribute data. However, anonymity is sometimes insufficient because attackers can still link the identity of the contributor to the reported data. For example, a report containing the house where a sensor reading was taken can leak information about the identity of the homeowner. Researchers have started using *k*-anonymity and spatio-temporal cloaking [10] to address this problem. Nevertheless, protecting privacy should not be limited to technical solutions, but should encompass initiating debates and proposing considerations about policies and regulations toward a common understanding of the rights of users to control and use their data.

5.6 Economic concerns

EI offers immense potential to consumers and service providers. However, for these innovations to evolve from ideas to tangible products for the mass market, many commercial issues require resolution. In data sharing among peers (e.g., for the data collected from personal devices for a community sensing purpose), the development of a solid economic model is highly important. This issue is even more critical when the devices (e.g., mobile phones, wearable sensors) have very limited resources, such as energy and storage capacity. Although enforcing cooperation and social connection can be the catalyst for this paradigm, additional strategies for incentives and reputation for data contributors are needed. Some ideas from the economic-relevant solutions devised in traditional P2P platforms and ad hoc networking systems can aid the resolution of this issue.

6 A reference embedded intelligence architecture

Based on the elaboration and discussion of EI, we propose a reference architecture to illustrate the key functional blocks of an EI-enhanced IoT system. It is intended to be the starting point that advances this new research area. We are also practicing the key ideas of the reference architecture in our ongoing EI related projects, which will then be presented.

6.1 The EI architecture

Figure 3 shows the proposed architecture, which consists of five layers: *sensing and local processing*, *data collection infrastructure*, *data aggregation and intelligence extraction*,

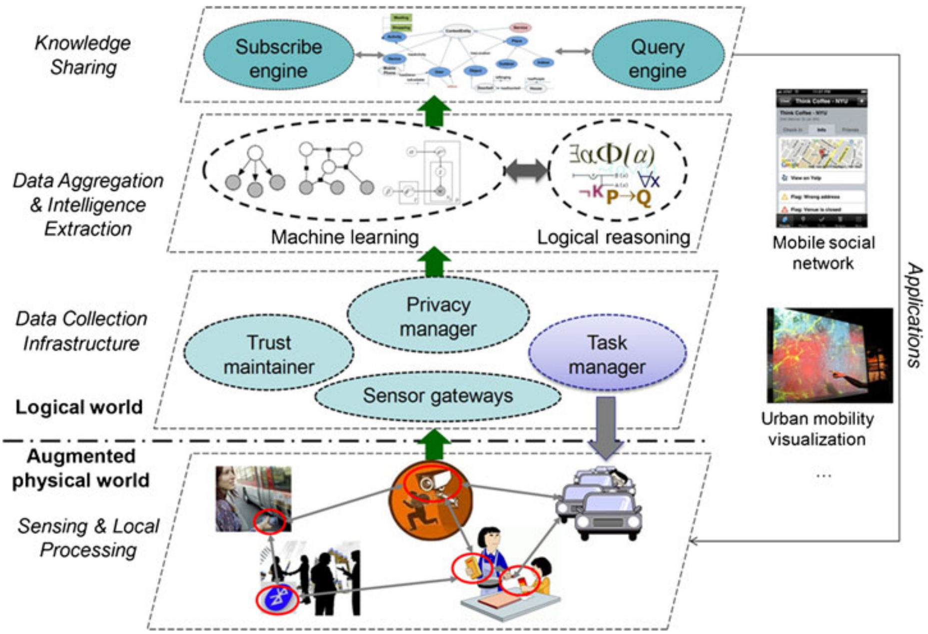


Figure 3 A reference EI architecture.

knowledge sharing, and *applications*. Instead of a purely centralized or self-supported method, a Hybrid Data Processing (HDP) solution is provided. We allow part of data processing tasks performed in smart objects to achieve local perception (e.g., recognizing personal activity on a mobile phone); local-reasoning results (sometimes raw sensor data) are transmitted to backend servers for group/community knowledge discovery (e.g., hotspot detection in a city) and information sharing (e.g., sharing current user activity with friends). The HDP solution significantly reduces the communication cost between clients and backend servers, and increases the resilience of the entire network. Our solution is similar to the split-design strategy used in the Darwin system, which advocates the splitting of data processing tasks in mobile phone sensing [40].

Layer-1: Sensing and local processing The first layer is a physical layer. Various everyday objects and devices connect themselves to large networks. They sense and record changes in the environment, as well as transmit raw sensor data or locally processed data (e.g., high-level features or micro-contexts) to backend servers.

Layer-2: Data collection infrastructure The second layer gathers data from trusted sensor nodes and provides privacy-preserving mechanisms for data contributors. The following components are involved:

- *Sensor gateway.* This component provides a standard approach (e.g., the web service techniques used in the SWE [51] and SenseWeb [23]) to data collection from various smart objects. The purpose of the gateway is to provide a uniform interface to all components (e.g., data processing and application components) above it. It also handles sampling optimism from smart devices.

- *Privacy manager*. Privacy is a major concern for personal data sharing. This layer provides data anonymization and privacy protection mechanisms before data are released and processed.
- *Trust maintainer*. A trust model is incorporated to ensure the trustworthiness and quality of data sources.
- *Task manager*. This component is significant to enable community sensing. It can analyze a sensing task from an application requester and assign it to the correct human contributor in terms of specified requirements, such as time window, location, and acceptance condition (see Section 5.1 for details).

Layer-3: Data aggregation and intelligence extraction This layer applies diverse machine learning and logic-based inference techniques to transform the collected low-level, single-modality sensing data into the expected intelligence. The focus is to mine the frequent data patterns to derive the three dimensions of EI at an integrated level.

Layer-4: Knowledge sharing The extracted knowledge can be shared and retrieved by authorized application entities. This layer employs semantic web and ontology techniques to enable unified knowledge representation, sharing, and retrieval (i.e., query and subscription).

Layer-5: Application layer This layer includes a variety of potential applications and services enabled by EI-enhanced IoT systems. We will present some of the applications we have developed in the next subsection.

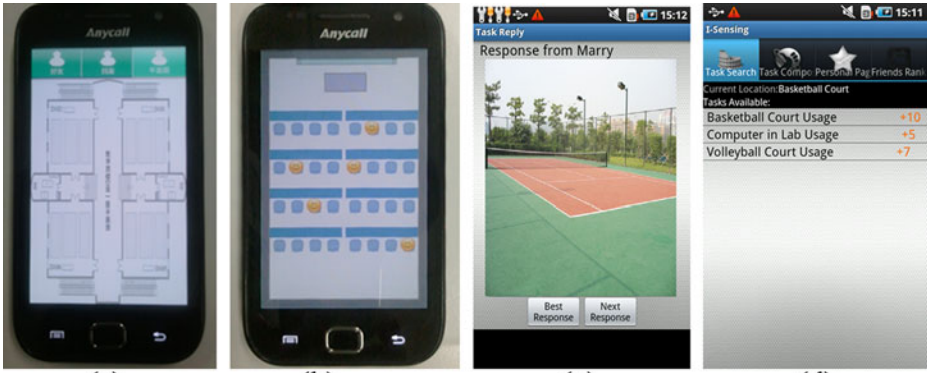
6.2 Ongoing projects and performance evaluation

The aim of EI is to augment existing IoT with user awareness, ambient awareness, and social awareness. We've developed a number of applications in the ongoing projects, which demonstrate the EI concept and practice the key ideas incorporated in the reference architecture. These applications also demonstrate the key concept of W2T, leveraging the data from the hyper world to realize organic amalgamation and harmonious symbiosis among humans, computers and things.

A. The Smart Campus

The university campus is a typical socially-active environment. To assist and enhance social interaction among students and staffs, we have designed and implemented a Smart Campus prototype [57] based on the EI reference architecture, under a collaboration project with Microsoft Research Aisa. The smart campus aims to benefit the social interaction with the introduction of participatory sensing (see Section 5.1) and mobile social networking (see Section 4.3). We have implemented two typical applications: *Where2Study* and *I-Sensing*.

The main purpose of *Where2Study* is to find a suitable place to study by using Wi-Fi positioning technology. It not only presents the navigation map of a building to help students find classrooms (Figure 4a), but also shows the status of all classrooms (full or free seats available), as shown in Figure 4b. Furthermore, *Where2Study* is also a mobile social networking application, which supports students to query the status and locate their friends in the university campus.



(a) (b) (c) (d)

Figure 4 Screenshots of Where2Study and ISensing.

People are often interested in the information about a place while they are not there. For instance, Bob is in the library and wonders whether the tennis court is occupied. *I-Sensing* is a campus-scale information sharing system based on participatory sensing, which allows users to share the status of public infrastructures in a university campus, such as play yards, libraries, coffee shops, and so on. Once a user posts a space-query to *I-Sensing*, the task manager (in Layer 2 of the reference architecture, *RA* for short) of *I-Sensing* will deliver the sensing task to a selected number of "observers" who are locating near that space (based on their GPS readings). Local observers can answer the query by either authoring text messages or simply taking pictures (as shown in Figure 4c). To encourage users to participant in more social interactions, social competition is also incorporated (see Figure 4d). In the future, we will analyze the interaction data from *I-Sensing* and estimate inter-personal relations (e.g., based on their common point of interests, such as tennis court) and recommend friends to university users.

A technical summary of the Smart Campus applications are given in Table 1. In short, by leveraging the mobile and static sensing devices in the campus, the EI-enhanced IoT will provide university users with ambient and social awareness.

B. User Awareness with Mobile Phone Sensing

As described in Section 3.2, human activities (e.g., walking, sitting, in conversation), user daily routines are important contexts in terms of user awareness. With the prevalence of sensor-equipped mobile phones, awareness of user on mobile phones

Table 1 Technical summary of three EI applications.

Applications	IoT devices	Scope	Intelligence learned	Intelligence extraction methods
Smart campus	Mobile phones, Wi-Fi receivers,	University Campus	Ambient contexts, Social connection	Wi-Fi positioning Participatory sensing
User awareness	Mobile phones	Human-centric	Human activity, daily routines	Decision tree (as the classifier)
Pervasive gaming	Ultrasonic sensors, Smart artefacts	Smart homes	Human activity	Rule-based reasoning

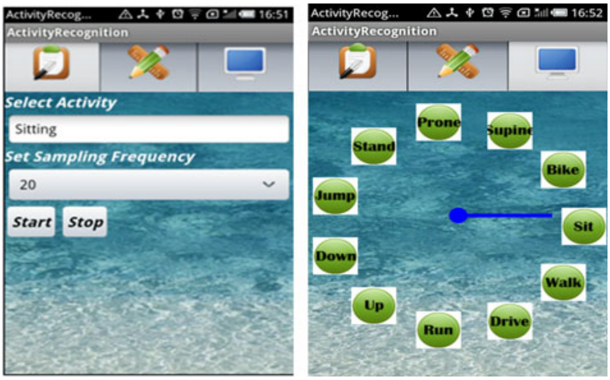


Figure 5 Screenshots of the human activity recognition: training (*left*) and classification (*right*).

(using accelerometer data) has become a hot research area. However, it is still a challenge due to the constraints of resources on mobile phones, such as battery limitation, computational load, and so on. To address these issues, we have proposed a scalable user awareness algorithm based on the HDP strategy (refer to *RA* in Section 6.1), whereby human contexts is derived from classifiers which execute in part on the mobile clients and in part on the backend servers. In detail, to reduce communication cost, raw sensor readings are processed by lightweight feature extractors (time features, frequency features) running on the phone, the extracted features are then transmitted to backend servers for user activity recognition and routing mining.

To demonstrate the effectiveness of the HDP strategy, we developed the Activity Recognition application on the Samsung i909 Android platform. Figure 5 (left) illustrates the data collection and training process of the application, while the classification process is shown in Figure 5 (right). The battery lifetime is used as a metric to measure the resilience of the system. Firstly, when all applications and sensors are turned off, the battery lifetime is about 30 h. This value declines to 11.2 h (when the sampling frequency is 10 Hz) when simply the built-in accelerometer is working (without running the Activity Recognition application). We further measured the battery lifetime

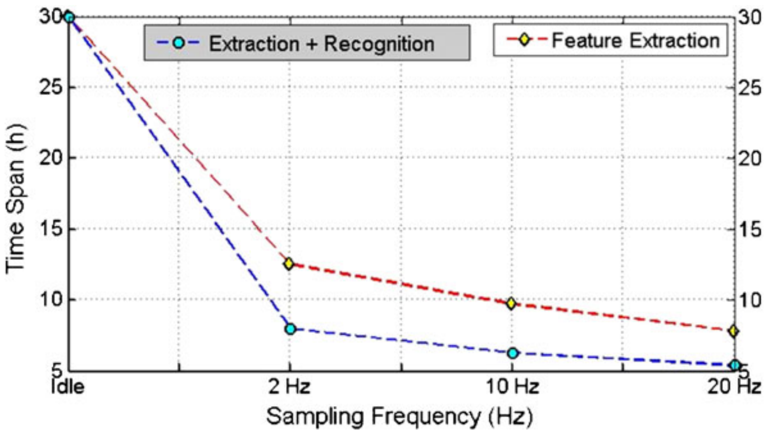


Figure 6 The battery lifetime under different data processing strategies.

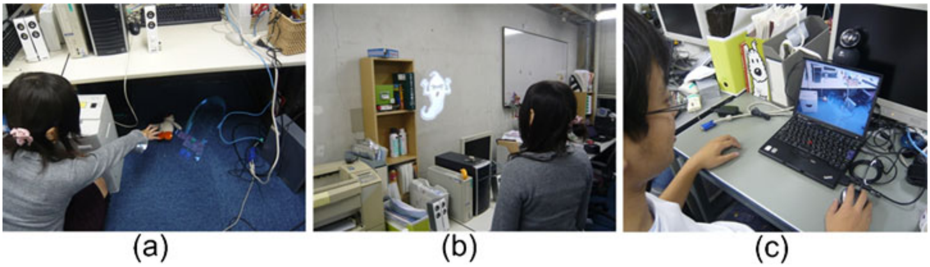


Figure 7 Screenshots of iFun play.

when 1) only feature extraction is executed on the phone and 2) both feature extraction and the classifier (based on the decision tree algorithm) are executed on the phone. As shown in Figure 6, when the classifier is mounted from the phone to the backend server, the mobile phone battery lifetime increases from 6.3 h to around 10 h (10 Hz), which indicates that the classifier consumes much higher power than feature extraction. This result also indicates that the HDP strategy can improve the energy-conservation performance of mobile phone sensing systems.

C. Pervasive Gaming

The development of IoT has propelled innovations on entertainment. Pervasive gaming is one of its productions. By blending of real and virtual elements and enabling users to physically interact with their surroundings during the play, people can become fully involved in pervasive games and attain better gaming experience. We have developed Treasure, a pervasive game playing in the context of people's daily living environments, which explores the interaction between human and smart indoor artefacts.

At the beginning of the game play, objects are hidden in different places of the house. Different objects play different roles (e.g., a monster, the treasure-box, the guide) in the game. When the players find a hidden-object (Figure 7a) or perform certain activities (e.g., open a drawer), the relevant multimedia action is presented to transmit information to the players (Figure 7b). Players need to hunt the 'treasure' to win the game. It should be noted that this game has the networked play mode, where a player *A* in a smart home can set a game in her house, and another player *B* can play the game online from a remote house, by using rotatable cameras installed in smart homes (Figure 7c). For example, B can prompt *A* to touch an object which might be the "treasure-box", as shown in Figure 7a.

Logic-based reasoning (in Layer 3 of *RF*) is used to extract high-level user contexts (e.g., finding an object, opening a drawer) from human-object interaction. The extracted contexts is represented in an ontology-based model (kept in a backend server), to support context sharing among heterogeneous smart homes (in Layer 4 of *RF*). The ontology is represented using the Semantic Web language OWL, and the inference rules

Table 2 Reasoning time in different scales of smart spaces.

Smart spaces	Size of ontology	Number of smart objects	Number of rules	Maximum reasoning time
Middle scale	2,000 triples	50	50	1.2 s
Large scale	3,000 triples	100	100	2.2 s

are represented using the Semantic Web Rule Language (SWRL, http://www.w3.org/Submission/SWRL/). Jess (http://www.jessrules.com/), a forward-chaining inference engine is used to execute inference rules. Experiments have been conducted to evaluate the performance of ontology-based context reasoning in different scaled smart spaces. The test environment is a 1.0 GB RAM PC with P4/2.0 GHz. We used two different-sized ontology and rule sets to evaluate the system scalability. The experiment results are illustrated in Table 2. It is not difficult to conclude that logic-based reasoning is affected by the ontology size and the number of rules applied. For most pervasive applications, as their real-time requirement is not likely to be critical, a perceivable delay (1 or 2 s) is acceptable. The system performance in large-scale smart spaces, however, can be improved when applying high-performance processors.

7 Conclusion and implications for the future

The EI introduced in this paper is expected to augment existing IoT systems with user, ambient, and social awareness under the grand W2T vision, and enable a wide range of innovative applications. For the EI to be fully employed, numerous challenges remain to be addressed. All these challenges present substantial research opportunities for academic researchers, industrial technologists, and business strategists. We have also presented a reference architecture and some of our ongoing practices, including the smart campus, mobile phone sensing, and pervasive gaming on EI-enhanced IoT. However, the development of EI presents both advantages and liabilities: although it connects people and makes lives more convenient, it impinges on privacy as never before. The future of EI is, in some ways, profoundly sobering, even as it promises infinite possibilities for business.

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