Living with Internet of Things: The Emergence of Embedded Intelligence

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***Abstract*— With the development of sensing, wireless communication, and Internet technologies, we are now living in a world that is filled with various smart things – the Internet of Things. This paper introduces and prospects an emerging research area – Embedded Intelligence (EI), which aims at revealing the individual behaviors, spatial contexts, as well as social patterns and urban dynamics by mining the digital traces left by people while interacting with Internet of Smart Things. The paper discusses the research history, characteristics, general architecture, major applications, and research issues of EI.**

Keywords- Internet of Things, Ubiquitous Computing, Social Computing, Embedded Intelligence, Mobile Social Networking

I. INTRODUCTION

With significant technological developments – as well as advances in sensors, wireless communications, and Internet – a lot of research areas have emerged, such as wearable computing, context-aware homes, mobile phone sensing, and smart vehicle systems. From those emerging areas, there is a clear trend to augment the physical devices/objects with sensing, computing and communication capabilities, connect them together to form a network, and make use of the collective effect of networked smart things − the Internet of Things. The Internet of Things is a technical revolution that represents the future of computing and communications, which brings us close to Weiser's vision on ubiquitous computing.

The incredible amount of information captured by trillions of smart things presents unprecedented opportunities to make sense of the world around us: *our movements in public places may be captured by surveillance cameras, our location trails can be recorded by sensor-equipped mobile phones, human activities can be inferred when we accomplish tasks with everyday objects, public transportation record can be kept while we use smart cards, real-time traffic information can be derived from GPS-equipped cars, buses and taxies...* Each of these transactions leaves *digital traces* that can be compiled into comprehensive pictures of human daily facets, with the potential to transform our understanding of our lives, organizations, as well as societies. While in the past years significant research efforts have focused on exploiting the connection techniques (e.g., RFID) and standards to enable the Internet of Things [1, 2], there is still little work that concerns study of the application of Artificial Intelligence and Data Mining techniques over the large-scale, multi-modal data collected from networked things to understand human life and social patterns.

Different from previous work, here in this paper we dedicate to review the development and research trends of an emerging field called "Embedded Intelligence (EI)", which aims at revealing the patterns of human/group behaviors, space contexts, as well as social and urban dynamics from the digital traces left by people while interacting with widely deployed smart things. A great variety of innovative applications are enabled by EI, in areas like mobile social networking, real-world search, city resource management, and environment monitoring. The paper gives a picture of the current state of the art on EI extraction. More specifically, it:

- Provides the readers with a description of the evolution and characteristics of three forms of intelligence that can be extracted from various smart things, saying, *individual intelligence*, *spatial intelligence*, and *social intelligence*;
- Reviews the enabled techniques and illustrates which are the major benefits of spread of this paradigm in everyday-life;
- Offers an analysis of the major research issues the scientific community still has to face.

Figure 1. Embedded intelligence extraction.

II. THE EVOLUTION OF EI RESEARCH

Research on extracting individual, spatial, and social intelligence from smart things has been going on for a long time (see Fig. 1 for an overview of EI research). This section we review the evolution of EI research in terms of distinct sensing sources.

A) *Surveillance Cameras*

Surveillance camera can be viewed as the first smart sensing object that is widely deployed in public and critical spots to detect *spatial contexts*, *human/group behaviors* and *social dynamics*. Many intelligent visual surveillance (IVS) systems have been developed by using single or a collection of surveillance cameras.

By analyzing the captured scenes from a fixed surveillance camera at a place, an IVS system can monitor the status of the space as well as human activities within the area. Chan *et al.* [3] developed a crowd counting algorithm based on Gaussian process regression to predict the number of people within an indoor environment. Saxena *et al.* [4] proposed a dedicated modeling approach to study scenario-based crowd behavior recognition (e.g., fighting, street passing), by extracting the crowd features such as crowd density and crowd motion dynamics (motion speed, direction, etc.). Along with the rising of social networking in recent years, some researchers have dedicated to social relationship extraction from the captured video sequences. For example, Ding and Yilmaz [5] have studied how to identify communities and find the leader of each community in video sequences, where they use two statistical learning methods to derive the affinity between individuals.

When surveillance cameras are widely deployed in a city-wide area and they connect, the combined power can help us to solve a series of social challenges, such as traffic forecasting and public safety. It has been reported that the Memphis city in US has used the CRUSH (criminal reduction utilizing statistical history) system developed by IBM to monitor the hot spots around the city and predict latest crimes [6]. CRUSH works by using a series of crime patterns learned from historical crime and arrest data, in combination with other factors like weather forecasts, economic indicators, and information on events such as paydays and concerts.

B) *Smart Indoor Artefacts*

With the development of wireless sensing techniques, massive cheap and tiny sensors like RFID and switches are deployed to augment everyday objects (i.e., the so-called indoor smart artefacts, such as information appliances, smart toolboxes, and smart cups [7]) in our daily living environments (to build the so-called "smart environments"). By analyzing the data from the attached sensors, smart artefacts can learn the context information (or extract underlying intelligence) in the smart environment and adapt its behavior to assist users.

To serve people well, smart artefacts need to firstly know the *physical location* of things (people and objects) so that they can record them and react accordingly. The Active Bats is an early system that uses ultrasonic sensors and the triangulation location-sensing technique to locate indoor objects [8], which enables location-based services like lost-object finding (e.g., finding a lost key). *Human activity* becomes another "intelligence" that can be learned from indoor artifacts. A number of activity recognition systems that focuses on accurate detection of human activities based on predefined activity models have been developed. For example, by embedding temperature and motion sensor into a cup, the Mediacup project can report not only the cup's situation, but also cup-relevant human activities, such as the cup being drunk from, played with, carried around, and filled up by a person [7].

Analyzing the data from a single smart artefact can merely reflect the human activity relevant to the object, fusion of the data from a collection of smart artifacts, however, can recognize more general human activities. For example, Philipose *et al.* explored techniques to recognize tens of human activities by analyzing people's use-trails of a number of RFID-equipped indoor objects, using the hidden Markov model (HMM) method [9]. The mined human activity information can be exploited to great societal benefits, especially in human-centric applications such as healthcare and eldercare, as demonstrated in [9, 10]. Nevertheless, smart-artifact based activity recognition is bounded to sensor-enriched indoor environments.

C) *Wearable Sensors*

The defect of indoor smart artifacts is remedied with the presence of wearable sensors, which transform people into "mobile" sensors for both personal context and ambient environment monitoring. Wearable sensors, such as accelerometers, pedometers, heart rate sensors, wireless webcams, microphones, are worn on different parts of human body to enable various human-centered services, such as *human activity recognition*, *routine discovery*, and *social context recognition*.

Researchers have prototyped wearable computer systems that use accelerometers, video, and other sensors to recognize user activities. For example, Bao *et al.* developed classifiers to detect physical activities (e.g., sitting still, standing, walking) from data acquired using five small accelerometers worn simultaneously on different parts of the body [11]. Instead of using classifiers to recognize a predefined set of activities, some other studies attempt to find unknown routine patterns (i.e., routine discovery) directly from low-level senor data leveraging unsupervised models. Huynh *et al.* introduced the topic model approach for modeling and discovering daily routines and implicit activity patterns from on-body sensor data [12]. Besides human activities, wearable sensors have also been explored on detecting the ambient context of a user. For instance, in a wearable-camera-based life recording system − Live Life [13], HMM technique has been used to learn situated social context (walking in the street, having coffee with friends) from wearable acceleration sensors and audio sensor.

D) *Mobile Phones*

Although wearable sensors are portable and promising, they are still not viewed as a "personal companion". Things change with the proliferation of sensor-enhanced mobile phones, where a number of sensors such as GPS receivers, Bluetooth/Wi-Fi, accelerometers, ambient light, and cameras are embedded. With these sensors, our phones can now track our movements through the physical world; they can record our social interactions, store our personal histories, keep tabs on our likes and dislikes, and track our Internet content consumption, app usage, purchasing behavior, and so on. The huge amount of multi-modal data collected from people's daily use of smart phones provide unprecedented opportunities to study *large-scale human behavior patterns*, *interpersonal interactions*, *social patterns* and *urban dynamics*.

- *Human behavior and social context*. As one particular type of wearable computer, it is not difficult to transplant human activity recognition method into mobile phones. The CenseMe project (http:// www.cenceme.org/) exploits off-the-shelf smart phones to automatically infer people's presence (e.g., running on the street) and then shares this presence through social network portals such as Facebook. SurroundSense uses a combination of sensed ambient light, sound and color information from mobile phones to predict the social context/situation (e.g., in a bookstore, eating in a restaurant) of their users [14].
- *Interpersonal interaction*. By logging various aspects of physical interactions and communication among people (e.g., co-location, conversations, call logs) and mining user behavior patterns (e.g., place of interests), EI nurtures the development of many social network services, such as friend recommendation and augmented online interaction. For example, the FriendSensing application [15] can recommend friends to its users by monitoring one's activities with mobile phones, including text messages, phone calls, and encounters.
- *Social behaviors*. Analyzing the data gathered from mobile phones at a community level can provide us insight into the underlying relational patterns (e.g., the interplay between different physical/social factors) and relational dynamics of groups, organizations, as well as societies. By taking advantage of the data collected by mobile phones, Reality Mining project (http://reality.media.mit.edu/) initiated at MIT intends to observe and characterize the social behavior of individual users and organizations (e.g., friendship, job satisfaction). The relationship pattern between the entropy of the locations the user visits and the number of social ties that user has in the social network was investigated by [16].
- *Human mobility patterns and urban dynamics*. Observing and modeling human movement in urban environments is essential for the planning and management of urban facilities and services. However, a key difficulty faced by urban planners and social scientists is that obtaining massive, real-world observational data for human movement is challenging and costly [17]. The large-scale sensing data from pocketed mobile phones, however, paves a way for studying human movements and urban dynamics. An interesting study based on the monitoring of 100,000 mobile phone users, conducted by Northeastern Univ. in US, discovered that human trajectory has a high degree of spatial-temporal regularity [18]. Real Time Rome (http://senseable.mit.edu/realtimerome/), initiated by MIT from 2006, is one of the pioneering projects that explicitly use mobile phone data to understand the dynamics of cities (e.g., movement patterns of people, spatial and social usage of streets and neighborhoods).
- *Environment context*. The nomadic, participatory, and in-situ nature of mobile phone sensing provides a new opportunity for environment monitoring. The Campbell research group from Dartmouth has done much research work on exploring the link between personal mobile sensing and public environment monitoring (e.g., air pollution distribution in a city) [19]. PEIR allows users to explore their own activity patterns and how their environmental impact and exposure relate to specific locations [20].

E) Smart Vehicles and Smart Cards

Accompanying with the rapid development of mobile sensing techniques, the prevalence of sensor-enhanced vehicles (e.g., GPS) and smart cards used on public transportation systems opens up another window to understand the "pulse" of a city. In their paper, Liu *et al.* reported on the use of multiple real time data sources (GPS data from taxi and smart card data from bus and metro) to understand daily urban mobility patterns and explored the relationship for mobility with land use (e.g., hot-spot detection), social-economic changes (e.g., prediction of residential and working area), underlying temporal and spatial dynamics of a city [21]. Kaltenbrunner *et al.* studied spatial-temporal human mobility patterns in an urban area by analyzing the amount of available bikes in the stations of the public bike sharing service "Bicing" in Barcelona [22]. Morency *et al.* investigated the spatial-temporal dynamics of urban public transit network leveraging the ten-month bus boarding records collected from a Canada city [23].

III. CHARACTERISTICS OF EI

EI aims at extracting individual behaviors, space contexts, and social dynamics from off-the-shelf or emerging smart things presented in the last section. The heterogeneous sensing sources have different attributes and strengths:

- Surveillance cameras enable the detection of individual/group activities and space context in public or critical spots, with a limited coverage.
- Smart artefacts are mainly deployed and used indoors, which is beneficial to infer indoor human activities.
- Wearable sensors and mobile devices are always user-centric, thus great at sensing individual activities, interpersonal interactions, significant user locations,

and public environment contexts in an anywhere, anytime fashion.

− Vehicles and smart cards are two major sources to extract human mobility patterns and city dynamics.

The various smart things weave themselves deeply into the fabric of everyday life. The diverse features of them, nevertheless, present us unprecedented opportunities to understand various aspects of interaction patterns between human and real-world entities, incorporating *human-object interaction*, *human-environment interaction*, and *human-human interaction*. These interaction patterns can be further elaborated into the three EI intelligence forms – individual intelligence, spatial intelligence, and social intelligence – identified in this article (see Figure 2). Following we characterize the attributes of the three intelligence types.

- *Individual intelligence* refers to the ability to understand personal contexts and behavior patterns. Examples include human/object location, human activity recognition, point of interests, daily routine patterns, and so on.
- *Spatial intelligence* concerns the status information regarding to a particular place, or the ambient environment context of a person. Examples include space semantics (e.g., the logical type of a place, such as a "supermarket"), ambient noise levels, space statuses (e.g., "occupied"), and so on.
- *Social intelligence* goes beyond individual contexts and reaches the levels of group and community. The objective is to reveal the patterns of interpersonal interaction, human mobility, and social behavior, as well as the dynamics of urban areas.

The learned EI can not only, from the micro-scale, improves the quality of human life by anticipating user needs and environmental changes, but also from the macro-scale, provides real time decision support for the crowd as well as urban managers.

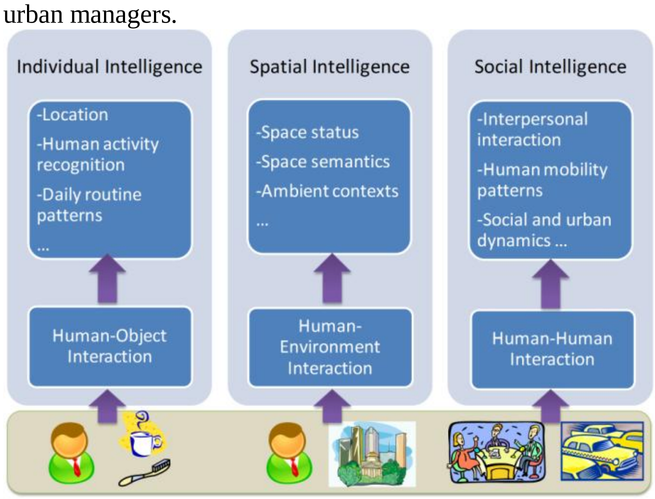

Figure 2. The characteristics of embedded intelligence.

IV. A General Architecture for EI Extraction

Research on EI extraction is in its early age. There is still little or no consensus on the intelligence extraction architecture. For example, it is not clear what architecture components (e.g., a human activity classifier) should be placed in local objects and what should run in back-end servers. In this section we propose our architectural viewpoint on EI extraction, which presents a starting point to move the field forward.

The proposed architecture is shown in Fig. 3, which consists of four layers: *sensor gateways*, *privacy management and trust maintenance*, *EI learning*, and *application layer*. A split data processing solution is explored: part of data processing tasks is performed in smart things to achieve "embedded intelligence" (e.g., recognizing personal activity on a mobile phone); local-reasoning results (sometimes raw sensor data) are transmitted to back-end servers for information sharing (e.g., sharing user location with his friends) and "collective intelligence" extraction (e.g., hot spot detection in a city). This solution can significantly reduce the communication cost between clients and back-end servers and increase the resilience of the whole network.

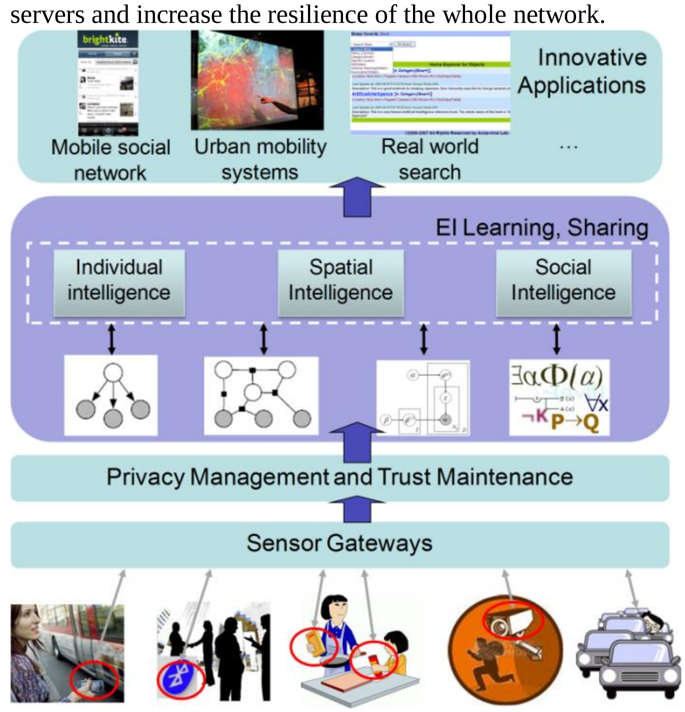

Figure 3. A general EI architecture.

− *Sensor gateways*. They implement sensor-specific methods to communicate with smart things and provide a uniform interface to all components above it. Smart things are at the edges of the whole network, and they can transmit either raw sensor data or local-processed data to back-end servers via sensor gateways.

− *Privacy management and trust maintenance*. Because privacy is a major concern for personal data sharing, this layer provides data anonymization and privacy protection mechanisms before the data is released and processed. A trust model is also incorporated to ensure the trustworthiness and quality of the collected data.

− *EI learning and sharing*. This layer applies diverse machine learning and logic-based inference techniques to transform the collected low-level single-modality sensing data into high-level features and expected EI, the focus is to mine the frequent data patterns to derive the individual/group behavior, space context, as well as social and urban dynamics at an integrated level. The collected or extracted EI can be shared and retrieved by authorized application entities.

− *Application layer*. It includes a variety of potential applications and services enabled by the availability of EI. We present some of them in detail in Section 5.

V. Innovative Applications

Potentialities of varied intelligence offered by smart things make possible the development of a wide range of applications. Many are the domains and the environments in which new applications would likely improve the quality of our lives: *at home*, *at work*, *while traveling*, *while communicating with others*, just to name a few. Here we present five major application areas.

A) Mobile Social Networking

Forging social connections with others is at the core of what makes us human. Mobile social networking (MSN) aims to improve social connectivity in physical communities (i.e., helping people stay in touch anytime, anywhere; recommending new connections) by leveraging information about people, places, and interpersonal interactions. Social Serendipity is one of the earliest MSN studies, which signals matching interests between nearby people who do not know each other to cue informal, face-to-face interactions [24].

When people connect, they influence and persuade. In MSN, peer influence becomes more important than ever, which offers a wealth of new business opportunities. Bottazzi *et al.* have proposed a place-dependent viral marketing solution that supports product advertisement distribution (e.g., forwarding promotional messages like coupons) among customers and their encounters in stores, following the word-of-mouth model [25]. Apps like GiveGiFi (http://www.givegifi.com/), let people leave digital gifts for purchases at places such as restaurants, hotels, bars, stores. Their friends can receive the “surprising” gifts when they “check-in” those places through FourSquare (a favorite MSN application, available at: http://foursquare.com/) the next time. It can be imagined that when all these MSN applications are at their disposal, businesses will bring the tools of direct-response marketing to physical places.

B) Real World Search

The increasing numbers of embedded sensor nodes being connected to the Internet makes it possible to observe an ever-increasing proportion of real world entities (i.e., people, places, events) via a standard Web browser. Unlike Google search in the virtual world, a real world search system can identify the real-time location, status and profile information of real world entities. Much previous work has been done on search the location of entities in small-scale, indoor environments. For instance, a searching system called MAX was built for human-centric, on-demand searching and location of physical objects with RFID tags [26] in smart homes. Our previous work Home-Explorer explored ultrasonic positioning technique to locate indoor objects, which particularly concerns the robustness of embedded sensors in real-world search [27].

Real world search is now moving from indoor environments to large-scale environments. As envisioned by Google researchers in the Nature magazine [28], search contents in the future will cover histories of interactions with colleagues, friends, and tracks of sensor readings from GPS devices, medical devices and other embedded sensors in the physical world. That’s to say, search will be extended to the whole society in the coming years. Early practice has been started up in Google, such as its real-time traffic condition service (http://maps.google.com/). Interesting work has also been done by the Sense Networks Inc (http://www. sensenetworks.com/). The Citysense application developed by this technology company is an innovative mobile application that supports real-time hot-spot discovery in urban areas, which can answer a compelling question – “*Where is everybody going right now?*”

C) Life-Logging

Human memory is fallible – most of us often find it hard to recall the details around what we have done and have to be done. It often is a serious inconvenience and negatively influences our wellbeing and also our performance in the workplace. With the development of wearable and mobile techniques in recent years, numerous digital lifelogging systems that aim to argument human memory through suitable means to capture, store, and access our daily life experiences (e.g., meeting friends on the road, conversations with a business partner) have been developed. Forget-me-not [29] is one of the earliest lifelogging systems, which uses a PDA to collect its user’s activities (e.g., location of a user, encounters) in the form of texts throughout the day. Live Life [13] has dedicated to capture of human experiences using a wearable camera. It associates collected video data with learned human activities and situated social environment from wearable acceleration sensors and audio sensor, which then can be used as contextual cues to augment data retrieval. In summary, we are stepping into the era of “the End of Forgetting.” While we outsource memory to smart devices, we may free up our brains for other information, such as complex social linkages.

D) Enterprise Computing and Groupware

Deploying and using of smart things in enterprises can facilitate the communication and collaboration among co-located or non-colocated employees. It can also help us understand organizational/societal behaviors in enterprises. For example, Microsoft’s SixthSense project uses RFID-tagged objects/devices to infer a range of enterprise intelligence such as the interaction and association between people and workplaces, which are then used for enterprise services like automatic conference-room booking [30]. Koji *et al.* use special designed work badges to study the relationship between productivity and interpersonal interactions in a workplace. The badges contain infrared sensors, microphones, accelerometers, and location sensors to record the location and duration of conversations between workers, their physical distance apart, encounters, upper body motions, and so on [31].

E) Urban Mobility Systems

Understanding human movement in urban environments has direct implications for the design of future urban public transport systems (e.g., more precise bus scheduling, improved service to public transport users), traffic forecasting (e.g., hot spot prediction), and urban planning (e.g., for transit-oriented urban development). There have been a number of studies that devote to extract city-wide human mobility patterns using large-scale data from smart vehicles and mobile phones. MIT's Real Time Rome project uses aggregated data from mobile phones, buses and taxies in Rome to better understand urban dynamics in real-time. Liu *et al.* reported that the spatial-temporal patterns of taxi trips are essential for a more refined urban taxi system, which allows us to control taxi supply according to the travel demand in space and time [21]. In [22], the learned spatial-temporal human mobility patterns enables the improvement of public bike sharing services, for example, the user can be informed about the best places to pick up or leave the bikes.

VI. RESEARCH ISSUES

Let us now turn our attention to key EI research issues. Many of these are directly motivated by the EI applications discussed earlier. To facilitate the development of EI systems, one fundamental issue is the collection and management of multi-modal data from different information sources. Other important issues include the better use of classifiers in terms of complex sensing contexts, and the security and privacy concerns raised by sensing and sharing of human daily experiences.

A) Human-Centric Sensing

EI allows the use of mobile sensing nodes (wearable sensors, mobile phones, and vehicles) to contribute data for community use (e.g., to sense and share the noise level from a particular street), i.e., the so-called "human-centric sensing" [19]. Comparing with static sensor networks, the involvement of humans as part of sensing infrastructure raises several new issues.

(1) Human roles. What roles should people play in human-centric sensing; for example, should they be interrupted to control the status (e.g., accept, stop) of a sensing task? Two different views were proposed by previous studies. The *participatory view* incorporates people into significant decision stages (e.g., deciding which application request to accept) of the sensing system. The *opportunistic view*, on the other hand, shifts the burden of users by automatically determining when devices can be used to meet application requests. There are limitations to both of the two views: purely participatory sensing places many demands on involved users; while the opportunistic approach suffers from the issues like potential leak of personally sensitive information and high computation cost on decision making (e.g., deciding whether the sampling condition is met). Future work should be done on balancing the control-load of users and computation-load of mobile sensing nodes while integrating proper protection mechanisms on data privacy.

(2) Sensing task assignment and data sampling. In human-centric sensing, using of mobile sensors form a highly volatile swarm of sensing nodes that can potentially provide coverage where no static sensing infrastructure is available. However, since there may be a large population of mobile nodes, a sensing task must identify which node(s) may accept the task. A set of criteria should be considered here to filter irrelevant mobile nodes: specification of the required region (e.g., a particular street) and time window, the acceptance conditions (for a traffic-condition capture task, only the phones out of user pocket and with good illumination condition can meet the requirement), and termination conditions (e.g., sampling period). Some preliminary work has been done on this. For example, [32] has proposed a task description language called AnonyTL to specify sample context for a sensing task. However, further efforts need to be done to improve the efficiency of the decision making process on task assignment and data sampling.

B) Data Collection, Representation, and Uncertainty

As in EI system, the data producers can be very different in terms of modality (e.g., mobile phones, vehicles, cameras), resource capabilities, data quality (high or low), and their sharing willingness. The data consumers are also heterogeneous in terms of running environments (applications that run locally or at community-level remotely) and data needs (some might need only high-level context information while others might need raw sensor data). The heterogeneity leads to several challenges on data management.

(1) The architecture for data collection: centralized or self-supported. Heterogeneous sensors are used in EI sensing, where some sensors may have almost no computing or storage resources, and some others are relatively better off. This situation leads to two distinct data collection methods: the *centralized* method transports all the sensor data to a resource-rich back-end server to perform all data processing; the *self-supported* method, nevertheless, builds the ability of data processing into the device itself. Both approaches have benefits as well as drawbacks, and present particular challenges and opportunities. For example, the collected data from a group of users 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. Though having the advantage of providing more scalable solutions, the *self-supported* approach may affect other applications' execution on the

device, mainly due to resource limitations. As reported in [33], running a simple Fourier transform on a mobile phone can impact other ongoing apps and can run too slowly to keep up with the stream of sampled data. Future work should consider a hybrid plan that considers the trade-off between the cost for on-the-phone computation and the cost for wireless communication with back-end servers. For example, in the architecture proposed in Section 4, we place part of the individual sensing task at the local side, which could produce a rather small set of result data to be transmitted to the server for community sensing.

(2) Standards on communication and knowledge representation. 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, the sensors might have different interfaces to access them. To hide much of this complexity, there should better be a standard sensor gateway that provides a uniform interface to all components (e.g., EI learning layer, applications) above it. Unified method for knowledge representation is also important. Raw data from different sensor sources should be transformed to the same measure metric, represented by a shared vocabulary/ontology to facilitate the learning and inference process, as demonstrated in previous studies like [34].

(3) Data uncertainty. The sensed data involves many sources of uncertainty, which may influence the accuracy of the subsequent EI extraction process: the embedded sensor can be broken or may report error data [27]; the sensing environment may generate much noisy data. Taking RFID-based human activity recognition for example [9], if several RFID-equipped objects are placed close to each other, the RFID-reader worn on the human body can detect them simultaneously, and thus affect the final recognition result. Though critical to many pervasive computing applications, not much research has been done in the detection and recovery aspects of faults or failures in challenging environments. Besides, collecting data from anonymous participants for EI extraction suffers from the data trust issue, if there lacks the control to ensure the source is valid. Therefore, certain reputation and guarantee mechanisms about the reliability of volunteer reports should also be integrated.

C) Harvesting EI from Low-level Sensing Data

To understand personal/community behaviors from gathered data, a set of classifiers should be explored for EI extraction. However, as the data processing task takes place out of controlled lab settings and is governed by uncontrolled users, many real-world issues arise.

(1) Lacking of a common model. In EI extraction, the number of individual/social behaviors to be detected is very large, and they are often performed in idiosyncratic ways in 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 the hand or in the pocket, which may impact the recognition accuracy when a common activity recognition model is used. In terms of this, it is better to train different classifiers that work in different contexts (even work for different users). 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. To deal with this problem (i.e., the sparse labeled data problem), it is promising to import mature semi-supervised or evolvable learning techniques. It is also attractive to leverage user collaboration/sharing in the data labeling process to reduce training time and labeling effort, as demonstrated by [19].

(2) Complexity and ambiguity. Accurate EI recognition is challenging because human activities in daily settings can be very complex. Successful research, however, has so far focused on recognizing simple individual/group activities, in lab environments. The complex nature of human activity, however, can pose many new challenges in uncontrolled environments. First, people can do several activities at the same time, in the same place. For example, you can answer a phone call while walk with your friend on the road. There is yet little effort on recognizing such concurrent activities. Second, similar situations or even the same one can be interpreted differently, and thus leads to the issue of ambiguity and system inconsistency. For example, the "picking up the wallet" action can belong to several activities, such as "leaving home" and "cleaning"; a group of co-located phones could compute different inference result about the social situation, such as "in a party" or "in a meeting", due to slight environmental differences.

Besides the above issues raised by the complex nature of individual/group activity, to understand or predict human/social behaviors at the community level, we should leverage ideas from recent social science and mathematical studies. For example, patterns such as power-law/small world topology have been found in networks ranging from friendships in schools to co-authorship networks in sciences [35]. Other techniques and models about large-scale networked systems should also been exploited in future EI research, such as random graph theory, statistical physical studies of complex networks, scale-free networks, just to name a few.

D) Security and Privacy

An easy to recognize fact is that sharing personal data with applications (e.g., contributing data to community-oriented services like city-wide pollution monitoring) can raise significant privacy concerns, with much information (e.g., location, point of interests) being sensitive and vulnerable to privacy attacks. The new security challenge introduced here is that: *how to protect 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. But anonymous is sometimes not enough, because attackers can still link the identity of the contributor from the data he/she reported. For example, a report containing Bob's house as the location where the sensor reading was taken can leak information about Bob's identity. People have started to use *k*-anonymity [19] and spatio-temporal cloaking [32] to deal with this problem. Besides exploiting privacy protection techniques, we should also devote to opening debates among viewpoints, policies and laws, toward a common understanding of users' rights to control their data and its use.

VII. CONCLUSION AND FUTURE VISION

Smart things are transforming humanity. The Embedded Intelligence (EI) reviewed in this article represents a new computing paradigm and an interdisciplinary research and application field. We expect that EI's scope will continue to expand and its applications to multiply. As we have discussed, the prevalence and development of EI still face challenges ranging from human-centric sensing/sampling, heterogeneous data collection and uncertainty management, to complex intelligence modeling/learning issues, which are expected to nurture a series of new research opportunities for academic researchers, industrial technologists, and business strategists as well. On the other hand, it is no doubt that the development of EI is a double-edged sword. While it is making people more connected and our life more convenient; it is eavesdropping on us and trespassing on our privacy as never before. The future of EI is, in some ways, profoundly sobering, even as it augurs infinite possibilities for business.

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