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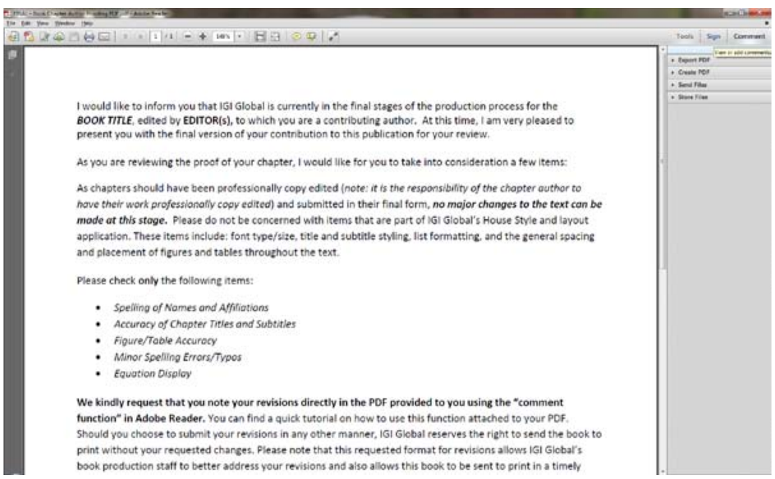

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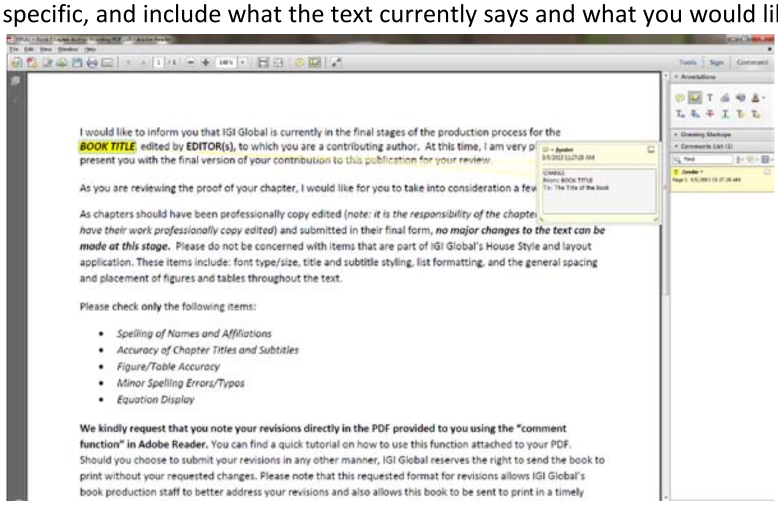

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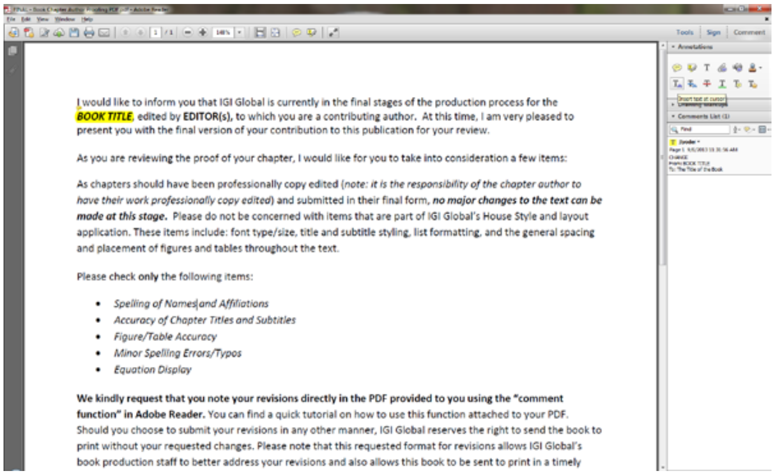

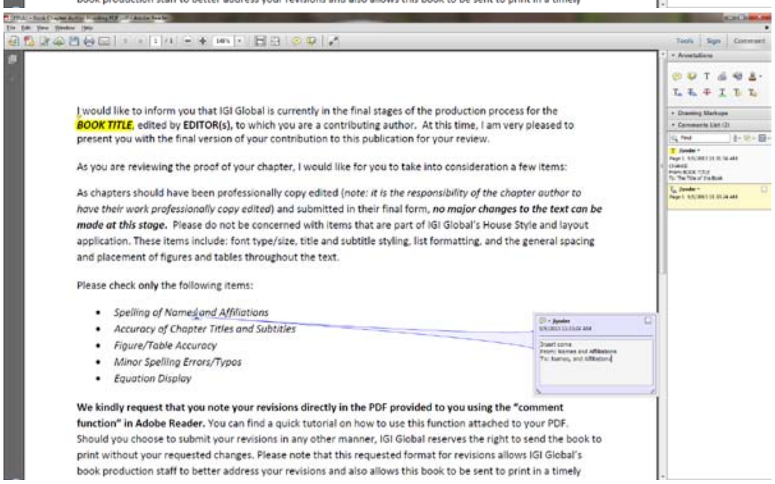

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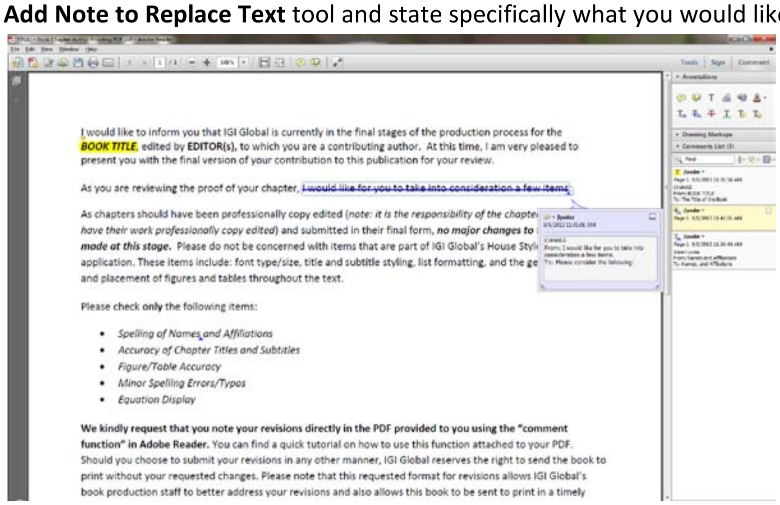

Encyclopedia of Mobile Phone Behavior

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Cognitive Phone for Sensing Human Behavior

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INTRODUCTION

The *Cognitive Phone* is argued to be the next step in the evolution of the mobile phone. A Cognitive Phone has the abilities of analyzing, storing, extracting and processing information by using the phone platform, including both hardware configuration and intelligent software. It derives the capabilities of sensing and inferring human behavior and social context from the own platform, connected sensors, and/or linked servers. Prof. Campbell Andrew at the Dartmouth College and Associate Prof. Choudhury Tanzeem at Cornell University first introduced the Cognitive Phone concept in 2012. They are also the leading experts in this area.

OVERVIEW

In 2005, Nokia initialized a SensorPlanet Project to use a phone as a sensor in various applications, such as healthcare, traffic monitoring, etc. Eagle and Pentland (2006) introduced reality mining technology based on Bluetooth enabled phones in 2006. Campbell and Choudhury (2012) first introduced the Cognitive Phone concept in 2012.

CURRENT SCIENTIFIC KNOWLEDGE OF COGNITIVE PHONES

The evolution of mobile phones and built-in sensors increase the capability of a mobile phone to become a cognitive platform.

Evolution of Mobile Phone Network

Mobile phone also known as handheld phone or cell phone was first was demonstrated by Motorola in 1973. Mobile phone was designed for the wireless communication of telephones. The first generation (1G) mobile telecommunication using analog technology was produced during 1980s. In 1991, the second generation (2G) digital cellular technology was launched in Finland on the GSM standard. Both 1G and 2G mobile phones are focusing on the voice service. From the third generation of mobile telecommunication, increasing data stream services are demanded by mobile phone users. Besides, users require more computation and connection capabilities to support the diverse mobile applications running on a mobile phone. In the fourth generation of mobile phone network, high speed connection is demanded to support the pervasive applications including online movies, high-definition mobile TV, video conferencing, 3D television and cloud computing. The advanced mobile networks enable

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Table 1. Hardware configuration of mainstream mobile phones

	Samsung Galaxy S5	Apple iPhone 5S	Nokia Lumia 1520
Communication			
Cellular network(4G LTE)	Yes	Yes	Yes
Wi-Fi	Yes	Yes	Yes
Bluetooth(4.0)	Yes	Yes	Yes
NFC	Yes	No	Yes
Computing			
OS	Android 4.4	iOS 7	Windows phone 8.1
CPU	2.6GHz/4 cores/32bit	1.3GHz/2 cores/64bit	1.5GHz/2 cores/32bit
RAM	2G	1G	2G
Storage	16-64G	16-64G	32G
Battery	2600mAh	1560mAh	2000mAh
Sensing			
Camera	16MP	8MP	41MP
Navigation	GPS, A-GPS, GLONASS	GPS, A-GPS, GLONASS, Cell ID, Wi-Fi positioning	GPS, A-GPS, GLONASS, Cell ID, Wi-Fi positioning
Gyroscope	Yes	Yes	Yes
Accelerometer	Yes	Yes	Yes
Magnetometer	Yes	Yes	Yes
Barometer	Yes	No	No
Light sensor	Yes	Yes	Yes
Proximity sensor	Yes	Yes	Yes
Humidity	Yes	No	No
Thermometer	Yes	No	No
Hart rate monitor	Yes	No	No

mobile phones online sensing capabilities in a rich context environment.

Mobile Phone Platform

With the high quality hardware platform configured into a mobile phone, the computing, sensing, and communication capabilities of a mobile phone are fast growing up. Leading hardware platforms enable cognitive phone ability with powerful CPU, featured sensors and several communication modules. The relevant hardware of the-state-of-the-art mobile phones are listed in the Table 1.

The most common mobile operating systems consist of Android, iOS, and Windows Phone. The operating systems provide APIs (Application programming interfaces) for accessing the internal resources of a mobile phone, which offers communication, computing, and sensing capabilities. The mobile phone communication modules consist of Cellular networks, e.g. LTE, 3G, short range wireless communication modules such as Wi-Fi, Bluetooth, and NFC. The state-of-the-art mobile phones are equipped with a quad-core CPU and a RAM more than 1 GB, which allow a mobile phone to run complex applications on-board.

The most important feature of all, a mobile phone contains varying built-in sensors, such as accelerometer, gyroscope, magnetometer, barometer, light sensor, proximity sensor, humidity sensor, thermometer, and even heart rate monitor, which enable the phone sensing capability. In addition, the location sensors such GPS and GLONASS provide the location of a mobile phone in the open sky area. Some cutting edge research also utilize the communication modules such Wi-Fi, Bluetooth, Cellular network, digital television signals, camera, motion sensors, light sensor to assist positioning in the GNSS (Global Navigation Satellite System) denied environment. In a word, sensing capability and location functionality provide the cognitive potential of a mobile phone.

Cognitive Capability

In our modern life, the mobile phone is now becoming a ubiquitous device for mobile sensing (Lane et al., 2010), mobile computing and wireless communication. It has been used to determine transportation modes (Reddy et al., 2010), detect human stress (Lu et al., 2012), happiness (Bogomolov, Lepri, & Pianesi, 2013), emotions (Rachuri et al., 2010) and sense human activities (Consolvo et al., 2008; Pei et al., 2012; Pei et al., 2013). It is a unique platform with low-cost sensors for inferring personal mobility contexts (Guinness, 2013) and cognizing human behaviors (Pei et al., 2013). Unlocking the powers of ubiquitous sensing, computation and communication, the scope of the mobile phone applications is now continuously extending at a fast pace. For hosting intelligent models running inside, mobile phone has a great potential to understand some simple living contexts of our daily life e.g. waiting for a bus, working in office etc. Of course, inferring living contexts is not a simple task because it needs to understand Where, Who, and What, and to some extent How and Why. This requires the technologies for sensing, modeling and inferring.

Sensing is a procedure of collecting various data using different sensors. These sensors include GNSS receiver; motion and orientation sensors such as accelerometer, magnetometer, and gyroscope; RF (Radio-Frequency) signal strength detector, and other sensors such as barometer, camera (Ruotsalainen, Kuusniemi, Bhuiyan, Chen, & Chen, 2013), audio recorder, ambient light detector, thermometer, and EMG (Electromyography) sensor (Chen et al., 2011). The sensor measurements are typically adopted for positioning, motion state recognition (Pei et al., 2012) and ambient environment detection in cooperation with a GIS (Geographical Information System) database e.g. a POI (Point of Interest) database.

Modeling is process of developing algorithms to form the models or classifiers based on training data sets. These models can be reference signal patterns e.g. fingerprints of the Wi-Fi signal strengths, probability distributions or other descriptive mathematical functions. They are the core elements of an intelligent system (Campbell & Choudhury, 2012).

Reality Mining

Reality mining aims at quantifying behavior in varying contexts. Researchers have been doing that for years in group level, for example, in traffic congestion and consumer behavior studies. With the help of a mobile phone, which more and more people are carrying along wherever they go, we can move to a personal level in reality mining. With the help of multisensory data, machine learning algorithms and massive storage and calculation capacity, we can make visible the daily behavior in individual, group, society, country and even world level. Endless amount of applications can be created based on measuring, feedback and interventions of daily habits, exercise, health, work routines, organizational communication, learning new skills, etc.

Several approaches to reality mining with mobile phones have been done already. Eagle and Pentland (2006) study consisted of 100 Nokia smart phones pre-installed with several pieces of software they had developed together with a version of the Context application from the University of Helsinki (Raento, Oulasvirta, Petit, & Toivonen, 2005). By continually logging and time-stamping information about a user's activity, location, and proximity to other users, the large-scale dynamics of collective human behavior could be analyzed (Eagle & Pentland, 2006).

In the Device Analyzer project, Wagner, Rice, and Beresford (2013) are building a dataset that captures real-world usage of thousands of Android mobile phones. Device Analyzer captures a time-series log of more than 200 different events in as much detail as is possible on Android. For example, Device Analyzer not only records when a device connects to a Wi-Fi access point; it records all the details captured whenever a Wi-Fi scan occurs, including AP MAC address, SSID, signal strength, frequency, and capabilities. Events recorded include changes to device settings (33 event types), installed applications (17), system characteristics (29), bluetooth devices (21), Wi-Fi networks (11), disk storage (6), charging characteristics (5), telephony (20), data usage (10), CPU and memory information for each running app and background process (11).

Miluzzo et al. (2010) presented the approach of using several mobile phones at the same time in Darwin system that can evolve, pool, and enable cooperation providing robust, efficient, and scalable sensing. Miluzzo et al. (2011) used accelerometer, audio, and localization sensor data for their VibN application to characterize the way people and communities interact with the locations they inhabit. In CenceMe application Miluzzo et al. (2008) built a personal mobile sensor system to share in social media where people are and what they are doing, including also randomly taken photographs.

Social Context Learning

Social context learning aims at defining where we are, where we are going, what we are doing and who we know and collaborate with. To define these we can use combination of data from all nearby located devices, their rhythm in time, colocation, headings and interpretations from the possible audio and visual sensors. Social context analysis could be used to recognize user needs, for timing suitable actions and information and adjust communication based on the user's situation. Several approaches to analyse the often noisy and complicated data in interpretation wise are presented next.

Adams, Phung, and Venkatesh (2008) presented online algorithms to extract social context: Social spheres were labeled locations of significance, represented as convex hulls extracted from GPS traces. Colocation was determined from Bluetooth and GPS to extract social rhythms, patterns in time, duration, place, and people corresponding to real-world activities. Social ties were formulated from proximity and shared spheres and rhythms. Social spheres meant where we go, social rhythms characterized what we do and social ties captured who we know.

Liang, Cao, and Zhu (2013) introduced the concept of social circle, to extract social patterns associated with multiple users and designed a system called CircleSense that supports accurate recognition of a generic set of social activities. The social circle could be obtained from user's proximity information, which was captured using the Bluetooth module embedded in a mobile phone to scan the nearby Bluetooth enabled devices. They applied metric learning technique and designed a fast gradient based optimization algorithm to minimize the classification error and incorporated temporal information to better differentiate social activities.

Lu, Pan, Lane, Choudhury, and Campbell (2009) created the SoundSense system, where the architecture and algorithms are designed for scalability and system uses a combination of supervised and unsupervised learning techniques to classify both general sound types (e.g., music, voice) and discover novel sound events specific to individual users. The system runs solely on the mobile phone.

Gatica-Perez (2009) presented a review of the current facets of research on automatic nonverbal analysis of social interaction in small group conversations from sensor data and concluded that despite the large progress in social psychology and cognition, no single theory can answer the questions of what specific nonverbal cues and what concrete integration mechanisms are used to make sense of each social situation. Kim, Chang, Holland, and Pentland (2008) opted for a portable solution for both sensing and displaying of group interaction, in which participants wear a badge that extracts speaking time, prosody, and motion, and displays measures of the interaction on a cell phone.

Health Care and Well-Being

Another promising application of the Cognitive Phone is for the purposes of health care and monitoring of well-being. Klasnja and Pratt (2012) reviewed the research literature related to the use of mobile phones for health interventions. The authors grouped the relevant research in order to create a taxonomy consisting of five intervention strategies:

1. Tracking health information,
2. Involving the healthcare team,
3. Leveraging social influence,
4. Increasing the accessibility of health information, and
5. Utilizing entertainment.

They also identified five features of mobile phones that were utilized in these works, including:

1. Text messaging (i.e. SMS),
2. Cameras,
3. Native applications,
4. Automated sensing, and
5. Internet access.

Incel, Kose, and Ersoy (2013) made a large review of the activity recognition systems that use integrated sensors in the mobile phone with a particular focus on the systems that target personal health and well-being applications. They summarized and compared results from 36 different research publications concerning these topics. The review includes a general description of the process of activity recognition and its relation to health and well-being. In particular, they highlighted the strong correlation between the level of physical activity and the level of well-being. Another related topic was the relation between daily routine and well-being. For example, in elderly patients suffering from dementia or Alzheimer's disease, a deviation from the normal daily routine can indicate a need for health care intervention. Lastly, they presented seven key challenges of activity recognition with mobile phones, including:

1. The effect of continuous sensing on the battery life of mobile phones,
2. The challenge of finding efficient classifiers that can run on mobile phones,
3. The "phone context problem," i.e. when the phone is not in a suitable location for the desired observation,
4. The burden of collecting a large amount of training data to train classifiers,
5. The fact that people do not always have their phone with them (including, e.g. leaving the phone on a desk while at work),
6. Persuading/motivating users to engage with health monitoring applications, and
7. The overall complexity of human behavior.

Despite these challenges, the abundance of research in this area suggests that health care and well-being is an important application area for the Cognitive Phone, especially in the years to come. As the technology of mobile devices continuously improves, many of the above issues may become less severe. The burden of training data may become less of an issue as the number of users scales up because the needed training data remains relatively constant, whereas the value of that data continues to increase. Lastly, the introduction of wearable devices, such as smart watches, bodes well for the future of health-care applications. Because these sensors are worn in known locations and are present with the user for an even greater portion of the day, items #3 and #5 are less of a concern. A few challenges will still remain unsolved, but this of the nature of nearly every area of technological development, and it does not prevent useful health care applications to be put into use.

Mobility Context Sensing

One important area of human behavior that the Cognitive Phone can contribute to understanding is that of human mobility. Using a number of sensors embedded in the mobile phone and an appropriate set of algorithms, the Cognitive Phone can recognize different modes of mobility, such as walking, running, driving a car, riding a bus, riding a bicycle, etc. Several research papers in recent years have demonstrated this capability, such as Duncan, Badland, and Mummery (2009); Oliver, Badland, Mavoa, Duncan, and Duncan (2010); Stenneth, Wolfson, Yu, and Xu (2011); Guinness (2013); Susi, Renaudin, and Lachapelle (2013); and Elhoushi, Georgy, Korenberg, and Noureldin (2014).

The most common approach for sensing mobility contexts using the Cognitive Phone is the supervised machine learning approach. In supervised machine learning, first a set of training data is collected, in which the sensor data are logged during periods of known mobility context. This type of data is often known as labeled data, as it is comprised of a set of sensor data with labels as to the corresponding true context. Usually a set of statistical attributes is formed by processing the raw sensor data. For example, instead of using the raw three-axis accelerometer signals, it is common to combine the three axes and compute the norm of the acceleration.

Next, the labeled data is used to train a so-called classifier, using one or more machine learning algorithm. These algorithms can be categorized based on the type of classifier that they are used to train, including decision trees, artificial neural networks, hidden Markov models, support vector machines, Bayesian networks, and instance-based classifiers, such as k-nearest neighbors. After training a classifier, it can be used on unknown data to detect the most likely mobility classifier. Most classifiers can be used in real-time or near-real-time to detect the activity of the mobile user, due to the low computational complexity of the classifier.

Guinness (2013) compared the performance of twenty different machine learning algorithms, as well as their computational complexity, using a relatively small dataset. This study found that the algorithm known as Random Forest performed the best, while still maintaining low computational complexity. This algorithm produces a set of decision trees, using a random subset of attributes during the "growing" process. The set of decision trees (called a "forest") is then used to classify the same data samples in parallel. The mobility context is determined by "voting" among the decision trees. The context receiving the most votes is assumed to be the actual mobility context of the mobile user.

In addition to the research-oriented studies listed above, several commercial mobile phone applications that monitor mobility context have become available in recent years. Notable examples include Moves, Human, and Companion. Although it is difficult to assess the size of this nascent market, Moves appears to be the forerunner, boasting more than 4 million downloads in April 2014 and being acquired by major internet company Facebook.

One drawback of commercial applications is that the underlying algorithms and techniques for detecting mobility context are usually considered proprietary and thus not disclosed. An exception to this is when algorithms are disclosed in patent applications. For example, US Patent 7,421,369 B2 describes the use of motion sensors and hidden Markov models to recognize the current motion of the user of the device. Nonetheless, it can be challenging to map specific commercial applications to specific patents, unless the company explicitly discloses which techniques are being employed.

AN IMPLEMENTATION EXAMPLE OF A COGNITIVE PHONE

Andrew Campbell and Tanzeem Choudhury introduced the Cognitive Phone concept in 2012. Even though the term Cognitive Phone has not been officially defined yet, from the examples given by Campbell and Choudhury (2012), the Cognitive Phone is argued to be the next step in the evolution of the mobile phone, which has the intelligence of sensing and inferring human behavior and context. We implemented a Cognitive Phone prototype to sense human behavior using various phone sensors in 2013 (Pei et al., 2013).

In the Cognitive Phone prototype, we describe the social context as a Context Pyramid which is shown in Figure 1, where the raw data from various sensors is the foundation of the Context Pyramid. Based on the Raw Sensor Data, we can extract Physical Parameters such as position coordinates, acceleration, heading, angular velocity, velocity, and orientation. Features/Patterns of physical parameters are generated for further pattern recognition in the Simple Contextual Descriptors, which infer the simple context such as location, motion, and surroundings. Activity-Level Descriptors combine the simple contextual information into the activity level. On the top of the pyramid, Rich Context includes rich social and psychological contexts, which is ultimately expressed in natural language.

The implementation of the Context Pyramid was broken down into three modules as shown in Figure 2. In module I, the social context in terms of position, motion, audio streams and visual contexts, were sensed by navigation and audio/visual sensors. The bottom three levels in the Context Pyramid are implemented in this module. Next, the social context and human behavior were modeled in module II, which realizes the top three levels of the pyramid. Mobile phone-based social applications ultimately use the human behavior models derived from module II, or the low level information from module I to demonstrate the use of sensing human behavior using indoor/outdoor seamless positioning technologies.

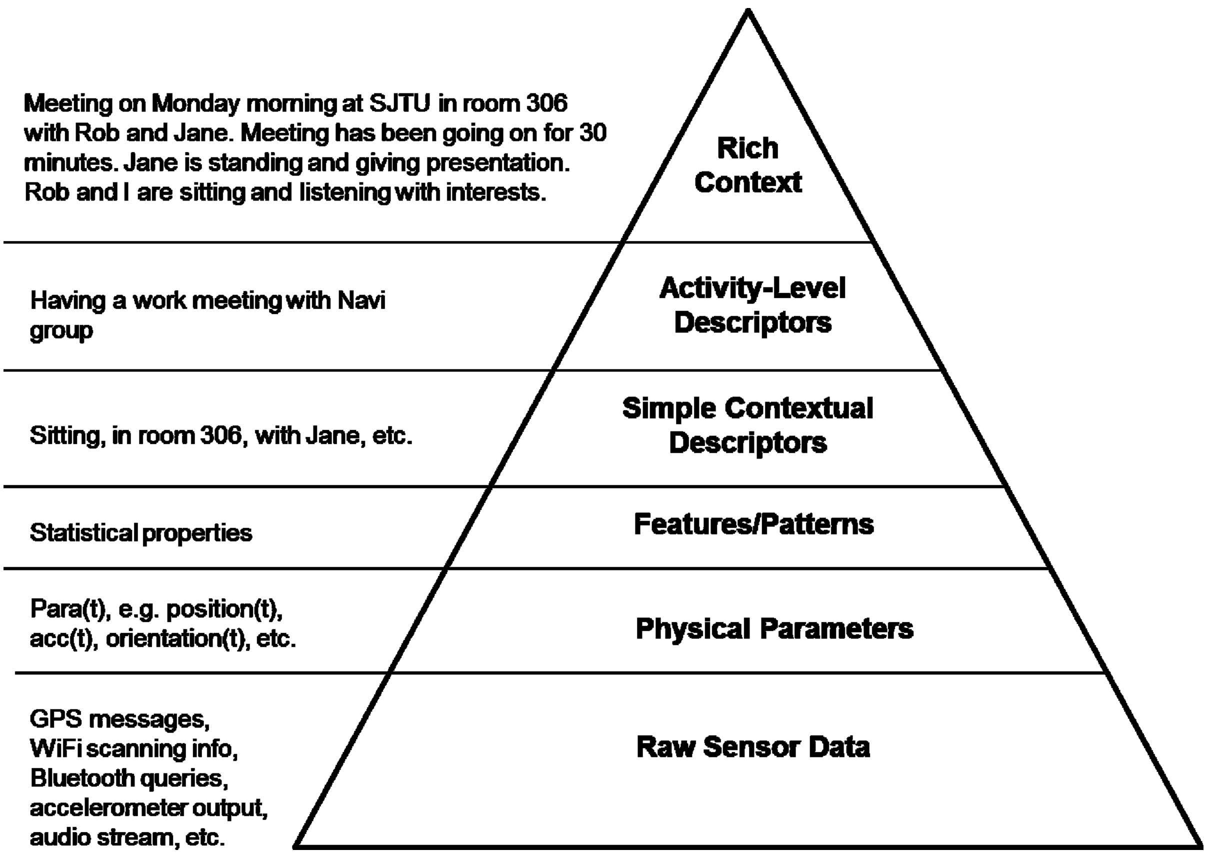
In order to implement cognitive applications, such as those shown in Figure 3, we combine the latest positioning technologies and mobile phone sensors to capture human movements in natural environments and use the movement information to study human behavior. Three key technologies are applied in this research: ubiquitous positioning, motion recognition, and human behavior modeling.

Modeling human behavior has great complexity, due to the wide range of activities that humans can undertake and due to the difficulties in systematically classifying these activities. Location-Motion-Context (LoMoCo) model (Pei et al., 2013) was proposed to combine personal location information and motion states to infer a corresponding context based on Bayesian reasoning.

LoMoCo Model

Given a specific context, a person always performs movements with some particular patterns. For instance, an employee usually sits in a break room while taking a break. He/she most likely stands in front of a coffee machine and shortly walks back to the office in a context of fetching coffee. In this research, we determine a context based on a LoMoCo model shown in Figure 3. In the LoMoCo model, a context (Co) is represented by location patterns (Lo) and motion patterns (Mo). Assuming that all the target contexts occur in n significant locations, we denote $L_n(t_i)$ as a context that occurs at L_n at the time epoch t_i. $P_l(n)$ denotes the density of the context that occurs at the location n. A location pattern (Lo) consists of the probabilities of all the possible locations. Similarly, motion patterns (Mo) include a set of probabilities for each possible motion state. $M_k(t_j)$ indicates that a context includes a motion state M_k of the time epoch t_j. In order to infer the context, the LoMoCo model in this paper is represented using Bayesian reasoning, which can not only

Figure 1. Context pyramid



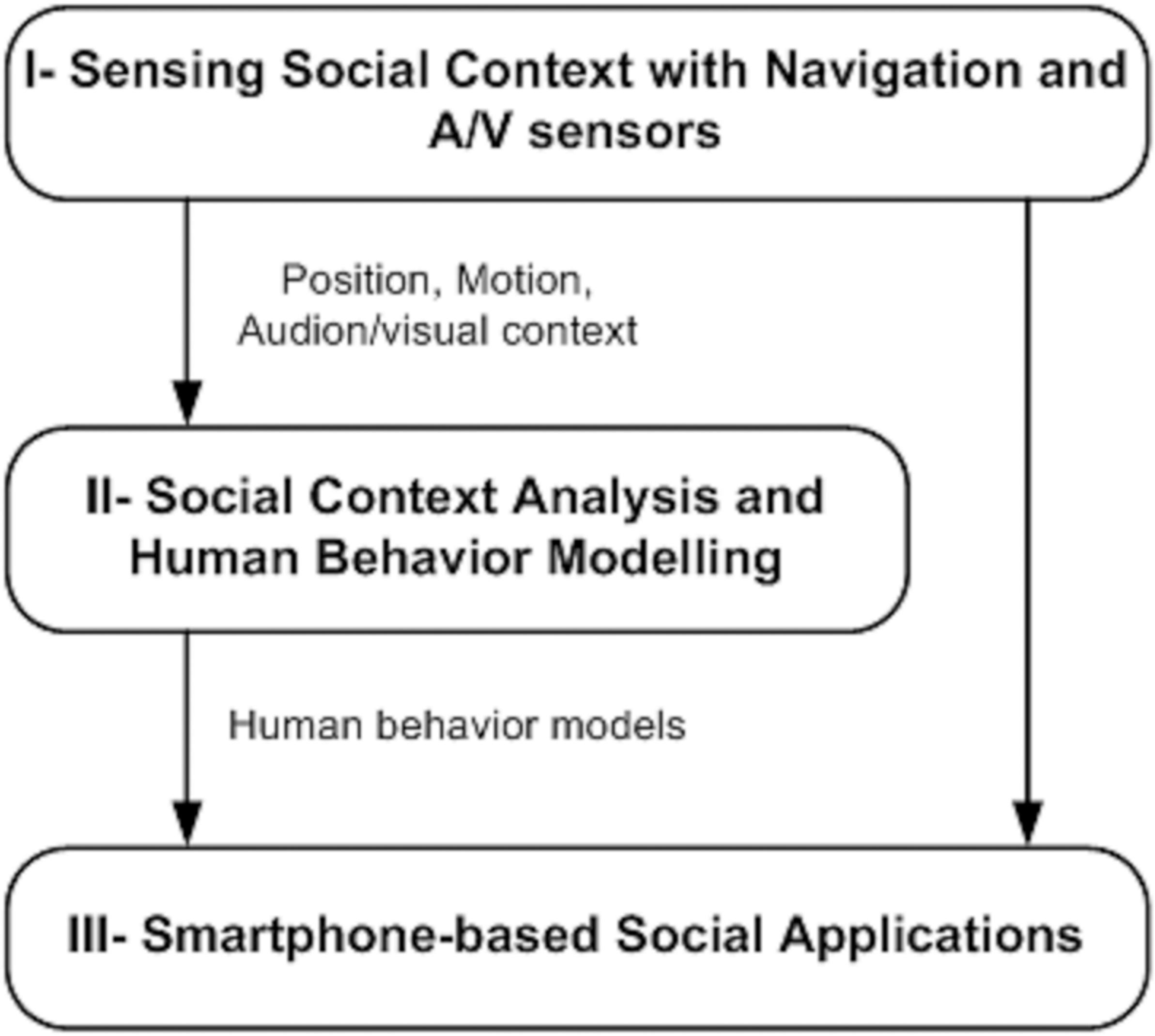
determine the context but also provide with the probability of a determined class.

FUTURE RESEARCH DIRECTIONS

In the future, the Cognitive Phone will achieve higher intelligence because of emerging sensors, advanced artificial intelligence, and big sensor data from large scale sources. Completing the LoMoCo-model with more sensors in the future can improve the current recognition accuracy and open completely new visions to behavior detection and change, by combining all the location, moving, body state, audio and video data together. For example, Han and Philipose (2013) outline the future of multisensory perception and their algorithms that would work locally in the user's mobile phone without cloud computing, when the next generation mobile phone memory, processing and battery capacity improves.

In persuasion technologies, to change people's behavior to positive direction, first step is making the current activities visible. Making daily activities visible can help recognize and change automatic mainly unconscious habits, that have been claimed to cover anything up to 50% of our daily activities (Wood, Quinn, & Kashy, 2002; Wood & Neal, 2007) and are common in mobile phone usage also (Oulasvirta, Rattenbury, Ma, & Raita, 2011). Massive multisensory behavior data enabled by new Cognitive Phones give numerous perspectives for making automatic habits and routines visible and to promote positive change in people's behavior. For example, feedback from daily activities of office workers can be used to train new habits of variable positions and physical moving during the work day, to avoid the adverse

Figure 2. Architecture of a social application



effects of too long stationary positions, which are considered as one of main threats for office worker's overall wellbeing in today's knowledge extensive work routines (e.g. van Uffelen et al., 2010) and in young people's daily activities (Biddle, Petrolini, & Pearson, 2014). For a collection of ideas for improving public health by use of reality mining see Pentland, Lazer, Brewer, and Heibeck. Work environment design could be improved with real mobile phone based data from worker's preferences and usage of office spaces. Health and sport related feedback is already giving knowledge of daily exercise in different moving modes: walking, cycling, running, swimming etc. New combinations of sensors and algorithms could revolutionize a whole tradition of behavior research, as Raento, Oulasvirta, and Eagle (2009) and Miller (2012) reviewed.

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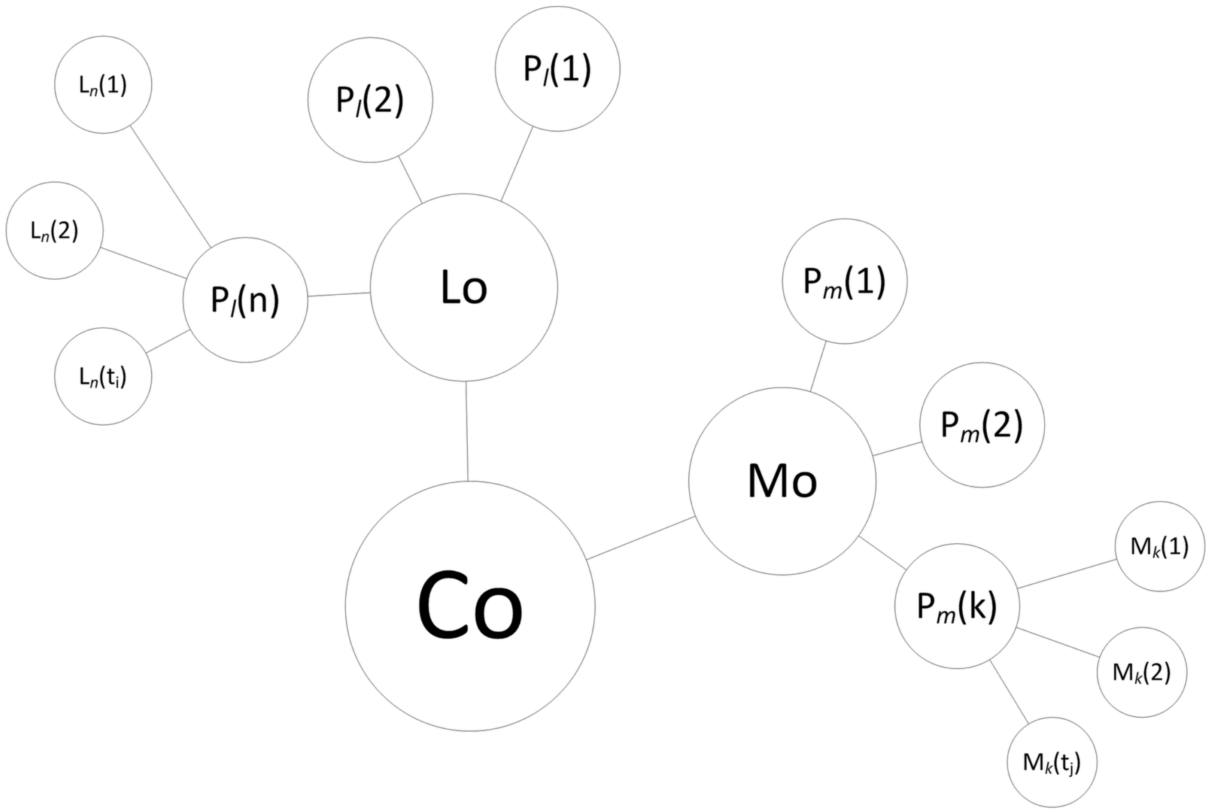
Figure 3. LoMoCo model



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KEY TERMS AND DEFINITIONS

Behavior Detection: A method of inferring human behavior by sensing the contexts around a user.

Cognitive Phone: A phone with the capabilities of sensing and inferring human behavior and social context from the own platform, connected sensors, and/or linked servers.

Localization: A technique for determining one's position.

Mobile Phone: A phone that can make and receive telephone calls over a radio link while moving around a wide geographic area.

Motion Recognition: A pattern recognition method of recognizing human motion states using sensors, such as accelerometers, gyroscopes, cameras, and so on.

Sensor: A device that detects events or changes in quantities and provides a corresponding output.