Chapter 2
Socially Aware Computing: Concepts, Technologies, and Practices

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Abstract The advances of pervasive computing technologies significantly enhance the capabilities for data capture, processing, and usage. The combination of pervasive computing and social computing leads to a new emerging research topic called 'socially aware computing'. This new paradigm aims to leverage the large-scale diverse sensing devices that can be deployed in human daily lives to recognize individual behaviors, discover group interaction patterns, and support communication and collaboration. Smartphones, which are equipped with a variety of sensors and are popular around the world, bring new opportunities for socially aware computing. In this chapter, we introduce the definition of socially aware computing, discuss the main research challenges, and present our work of implementing socially aware computing by using smartphones.

2.1 Introduction

Ubiquitous computing has been proposed and evolved for more than 20 years. A lot of technologies have been investigated and various applications have been developed, such as smart home, smart classroom, and smart meeting. With the rapid advances of embedded devices, wireless sensor networks, and mobile computing, more and more ubiquitous intelligent systems are being deployed in human daily lives. Such systems are integrated with the capabilities of sensing, computation, and communication, which significantly enhance data capture, processing, and usage in ubiquitous computing. Furthermore, it is now possible to sense social context and support social activity.

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In 2005, Alex Pentland proposed the notion of socially aware computing in his paper entitled "Socially Aware Computation and Communication" (Pentland 2005). It aims to capture, quantify, and visualize social context, such as tone, gesture, and posture for enhancing human social interaction. In 2009, David Lazer et al. (2009) proposed using massive data streams collected in the real world for understanding individuals, organizations, and even our society. Their motivation and target are very similar to those of socially aware computing.

Social awareness is a concept that comes from sociology. It is used to describe the capability or phenomena of social communication, such as knowing what behavior is accepted in the society and following the specification. In the area of computer science, social awareness refers to sensing and reacting to social context by computer systems. A system with social awareness can help people understand the current situation, improve their social communication skills, and facilitate efficient social interaction.

According to International Data Corporation (IDC), the number of mobile phones in existence in 2010 was three times the number of personal computers. The number of mobile phones used around the world then reached 5.9 billion in 2011. On the other hand, smartphones are becoming cheap and are now becoming more popular.

Smartphones are equipped with a variety of sensors, such as accelerometer, GPS, digital compass, microphone, camera, etc. More importantly, smartphones are programmable, which enables the development of context-aware applications based on the built-in sensors. Smartphones bring new opportunities for socially aware computing, such as activity recognition, large-scale sensing, mobile social networking, etc.

In this chapter, we first introduce the definition of socially aware computing, then describe the main research issues associated with it. We then present our work of implementing socially aware computing by using smartphones, specifically activity recognition based on smartphones, enhancing social interaction with smartphones, and understanding social relationship with mobile phone data.

2.2 What Is Socially Aware Computing?

2.2.1 The Origin of Socially Aware Computing

Understanding the behavior and interaction of human beings has been a fundamental research topic for many years. Most of the existing studies investigate social relationships based on user survey data (Carley and Krackhardt 1996; Vaquera and Kao 2008). They are constrained in accuracy, breadth, and depth because of their reliance on the data derived from using a self-reported questionnaire. This kind of data has several limitations. First, it is subjective, as the input might be influenced by the subject himself/herself, e.g., concealing the facts for certain reasons. Second, it is a snapshot that is not dynamic or real time. Furthermore, the self-reported survey cannot be conducted with large-scale populations because that results in controlled and limited data.

With the emergence of the Internet and the Web, it is possible to obtain large-scale data for analyzing online behavior and social networks. Tang et al. (2012) propose a method to detect community based on social media data acquired from the Web, such as BlogCatalog and Flickr. Lin et al. (2009) use the Blog and DBLP data to discover communities and analyze community evolution. Chen and Saad (2012) adopt the citation network and trust network on the Web to extract community. However, online behavior is virtual, which makes it essentially different from the temporal–spatial human behavior and interaction in the real physical world.

By using mobile and pervasive computing technologies, it is possible to obtain real-world sensing data for sociological studies. Compared with the self-reported data, the automatically captured data has many advantages: it is objective (or honest) without user bias, and the continuous field data is particularly appropriate for longitudinal studies of human behaviors in their daily lives. Moreover, the data capture can be automatically performed in a large-scale population, and different data processing algorithms can be compared based on a common data set. Leveraging pervasive sensing to collect and analyze the "digital footprints" at community scale, social and community intelligence can be realized (Zhang et al. 2011).

Socially aware computing is essentially the analysis of human beings and their societies, as well as the development of pervasive computing technologies. Therefore, we can say that it is the convergence of social computing and pervasive computing.

2.3 The Definition of Socially Aware Computing

Here we give our general definition of socially aware computing. *Socially aware computing aims to leverage large-scale, dynamic, continuous, and real-time sensory data to recognize individual behaviors, discover group interaction patterns, and support human communication and collaboration.*

The large number of various sensing devices, such as ubiquitous sensors (e.g., RFID, motion sensors, microphone, camera, etc.) and mobile phones (recording the logs of GPS, calls, and messages), combined with e-mail and Web (e.g., DBLP, BBS, social network sites, blogs, Wiki), offer the in situ data for analyzing human behavior and interaction. In addition to analysis, socially aware computing also emphasizes intelligent assistance and support of human behavior and social interaction from the individual, group, and society perspectives respectively.

Figure 2.1 shows the relationship between socially aware computing, physical world, and macroscopic society. By using various large-scale sensors, socially aware computing captures sensory data from the physical world. After processing the sensory data, socially aware computing provides decision support for macroscopic society. On the other hand, socially aware computing receives theoretical guidance from macroscopic society, and gives direct effect to the physical world through intelligent devices and actuators.

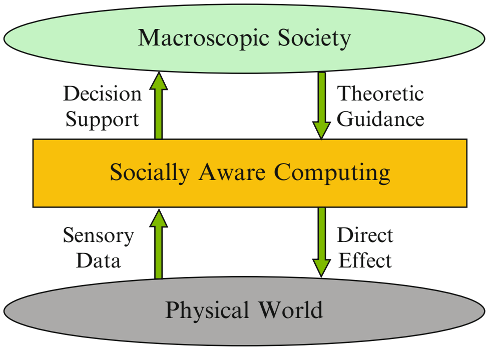

Fig. 2.1 The relationship between socially aware computing, physical world, and macroscopic society

2.4 Main Research Issues of Socially Aware Computing

There are basically five research topics related to socially aware computing: large-scale pervasive sensing, activity and interaction analysis, social interaction support, software framework and methodology, and applications.

2.4.1 Large-Scale Pervasive Sensing

Large-scale pervasive sensing is required for capturing human beings and their society. Three main sensing data sources are mobile sensors, social web, and static sensing infrastructure. Mobile sensors are attached to moving objects, e.g., vehicles and persons. For instance, camera and GPS loggers equipped with a shuttle bus are mobile sensors. A smartphone with various kinds of built-in sensors is a typical mobile sensing platform. Social web refers to the web sites through which people maintain their social networks and interact with each other in the cyber space. The online interaction and user-generated content can be used to analyze human behavior and relationship. Sheth (2009) label Web 2.0 service users as “citizen sensors”, and have worked on social event detection from user-contributed contents. Static sensing infrastructure is deployed in our daily life statically, such as surveillance cameras, environmental sensors, and positioning sensors. For instance, it is possible to detect abnormal events using the surveillance cameras widely installed in a city. Temperature, light, and humidity sensors are also widely used for environmental monitoring, for example, to detect a forest fire.

As the sensing data comes from different sources, before it can be used for analyzing human behavior and interaction, several data management operations should be conducted.

2.4.1.1 Multimodal Data Processing

The sensing data can be in different modalities, such as video, image, audio, and structured text. Different sensor types have different attributes and capabilities, such as varying accuracy in sensing the physical and virtual world. Extracting features from the multimodal data is the basis for high-level processing. Another interesting but challenging piece of work is to discover the relevancy from different data sources and modalities.

2.4.1.2 Semantic Representation

To make the data understandable for the machine and usable for external applications, raw data from different sensor sources must be transformed to the same metrics and represented by a shared ontology.

2.4.1.3 Large-Scale Sensing Data Fusion

Sensing data usually has noise, uncertainty, and varying accuracy. Isolated sensing data provides limited information in a complex scenario. Data fusion can be used to address this issue. On the other hand, it is better to fuse the data in order to decrease the data size in transfer and storage.

2.4.1.4 Large-Scale Sensing Data Storage

The three main pervasive sensing technologies mentioned above lead to a very large amount of data generation. Furthermore, the sensing data is continuously generated, which poses hard challenges for data storage, backup, and addition. Data access, i.e., searching or querying particular information from the large sensing data efficiently, is a challenging research topic.

2.4.2 Activity and Interaction Analysis

With the sensing data, it is possible to recognize individual activity and analyze group interaction as mentioned below.

2.4.2.1 Individual Activity Recognition

Activity recognition has been drawing increasing interest from the researchers in the fields of artificial intelligence, personalization, and ubiquitous computing. Chen et al. (2012) present a comprehensive survey to examine the development and current status of various aspects of sensor-based activity recognition. From the viewpoint of sensor usage, activity recognition can be divided into two categories. One is monitoring the movement of the human body by using sensors that are placed on the body. The recognized activities include walking, running, scrubbing, and exercising.

The other approach is monitoring how people interact with objects (e.g., how people move things, usage of objects). Usually this approach is effective in recognizing activities such as grooming, cooking, phoning, toileting, and washing hands. It requires that objects are instrumented with tags, and that users wear an RFID reader affixed to a glove or a bracelet. Patterson et al. (2005) perform fine-grained activity recognition (i.e., not just recognizing that a person is cooking but determining what they are cooking) by aggregating abstract object usage.

The inference model is the key issue of activity recognition. In terms of a learning model, the approaches can be grouped as supervised learning-based activity recognition and unsupervised learning-based activity recognition. The former one is basically a classification problem. It first uses a number of records composed of features and activity labels for training, then it uses the learned model to predict an unlabeled record. The classifiers can be static or temporal. Static classifiers include support vector machine (SVM), naïve Bayes, Bayesian network, and decision tree, while hidden Markov model (HMM), conditional random field (CRF), and dynamic Bayesian networks (DBN) are temporal classifiers. The unsupervised learning-based methods use clustering or mining for activity detection. Phung et al. (2009) recognize user motion state, significant places which the user visits, and user rhythms by using a density-based clustering technique based on Wi-Fi observations. Gu et al. (2009) build activity models by mining a set of emerging patterns from the sequential activity trace only, and apply these models in recognizing sequential, interleaved, and concurrent activities.

Current work on activity recognition has mainly focused on simplified use scenarios involving single-user single-activity recognition (Chen et al. 2012). In real-world situations, human activities are often performed in complex ways. For example, a single user performs concurrent, interleaving, and multi-goal activities. Multiple users perform a cooperative activity. A major issue when observing multiple people is the data association problem: what observations belong to which person? Another complex scenario is recognizing abnormal activities, which is a particularly important task in security monitoring, where suspicious activities need to be dealt with, and healthcare applications, where assistance needs to be provided for incapable users. The most challenging issue of abnormal activity recognition is the unbalanced data problem. A much larger proportion of sensing data is about normal activity, while the data for abnormal activities are extremely scarce, which makes training the classification model quite difficult.

2.4.2.2 Group Interaction Analysis

Compared with individual activity, group interaction is a higher level social semantic. Based on the extracted individual behaviors, social network analysis, machine learning, and data mining techniques can be used to analyze group interaction. Main research topics include group relationship reasoning, interaction pattern discovery, community structure detection, and evolution analysis.

Group relationship can be inferred from sensory data. Eagle et al. (2009) propose to infer friendship based on proximity (via Bluetooth scan). It is based on the common sense and experience that friends usually spend time together in the same physical sites. By using the extra-role factor, i.e., off-campus proximity, they can predict most reciprocal friends and non-friends.

Human interaction is one of the most important characteristics of group social dynamics. Yu et al. (2010a) present a multimodal approach for detecting human interaction based on a variety of contexts, such as head gestures, attention from others, speech tone, speaking time, etc. Discovering interaction patterns is useful for understanding how people interact within a group or with the people in another community. Yu et al. (2013) propose tree-based mining algorithms for discovering patterns of group interaction flow and interaction network in meeting discussion.

Community structure is useful for understanding how people are organized and how information is propagated in the community. Social network analysis methods are often adopted in this study. Onnela et al. (2007) analyze the structure and tie strengths of social and communication networks by using the call records of millions of mobile phones. They find a coupling between interaction strengths and the network's local structure, e.g., social networks are robust to the removal of the strong ties but fall apart after a phase transition if the weak ties are removed.

Investigating how a social group evolves is important to understand community dynamics and predict its future structure. Investigating community evolution is challenging due to the difficulty in obtaining dynamic and continuous human interaction data reflecting the evolution process in the real world. Palla et al. (2007) investigated the stability, group lifetime, and member abandonment in social group evolution by using both co-authorship network and mobile phone call records. Kossinets and Watts (2006) analyzed social network evolution by using e-mail contact data, and found that network evolution is dominated by the network topology and the organizational structure in which the network is embedded.

2.4.3 Social Interaction Support

Differently from social computing and social network analysis, which mainly focus on data analysis, socially aware computing aims to support human communication and collaboration based on the sensed activity and interaction. Thus, social interaction support is the core function in realizing social awareness. It serves as the interface between human beings and the system. The underlying techniques are personalized recommendation, social status visualization, group collaboration, and smart decision-making.

VENETA (Arb et al. 2008) is an application that recommends new friends based on a mobile social networking platform. It uses a decentralized method to explore the social neighborhood of a user by detecting friends of friends that are in the user's current physical proximity. Whenever two mobile phones come into Bluetooth connection range, they compare their contact book entries. If neither of the users appears in the other's contact book (i.e., the users are not friends already) and they share at least one common contact, then the two users are identified as friends of a friend. The objectively mined friendship could nudge a user to be aware of a (statistical) relationship with others.

Yu et al. (2010b) present a graphical user interface for visualizing group social dynamics in a meeting. It helps with meeting people in the organization, and improves people's meeting participation skills. For instance, knowing the current status of the meeting (e.g., did all members agree on a conclusion, who was quiet, who was extroverted), the organizer can make some adjustments to make the meeting more efficient. On the other hand, through interaction visualization, the members become aware of their own and others' behavior in a discussion (e.g., one person speaks for a long time, two people always discuss in a subgroup), and can then make changes to increase the group's satisfaction with the discussion process.

DeaiExplorer (Konomi et al. 2006) extracts social networks from DBLP, a web-based publication database. It builds personal connections from historical records of research activities by taking into consideration co-authoring, publishing in the same proceedings, citation, co-citation, and bibliographic coupling. The extracted social networks are revealed on a big display installed at a conference venue. The co-located conference participants can discover interpersonal connections, and find each other in the physical space through RFID technology. Combining the Web data and physical sensing data, the system successfully supports academic collaboration.

2.4.4 Software Framework and Methodology

To facilitate socially aware computing application development, testing, and deployment, software framework and infrastructure are needed. It offers systematic support for fulfilling common functions, such as heterogeneous data management, social context inference, personalized recommendation, information visualization, etc. Software methodology, i.e., principles guiding the design of models and algorithms, is also required. Furthermore, evaluation standards and methods are required for evaluating socially aware systems. There have been several attempts to develop the software framework and methodology of socially aware computing.

WearCom (Kortuem and Segall 2003) is the wearable community design methodology which facilitates application creation, and provides a framework for investigating the social and technical issues involved. Wearable communities denote the social networks that might emerge when enough people use wearable computing technology throughout their daily lives. WearCom supports an exploratory design approach based on rapid prototyping of wearable community systems. It integrates social and technical concerns, and guides designers from scenario development to implementation. WearCom provides a design language, a design process, and a software platform. The design language permits the specification of important design decisions. The design process outlines an iterative sequence of individual design activities, each of which generates a specific design artifact. The software platform supports the implementation and execution of proactive, presence-aware wearable community applications. Furthermore, six design principles are proposed that contribute to successful wearable communities. Developers can apply these guidelines to evaluate existing designs, guide the design process, and educate designers about the characteristics of successful wearable community systems.

Raento and Oulasvirta (2008) indicate that social awareness applications are based on the idea of a group sharing real-time context information via personal and ubiquitous terminals. Based on the social psychological findings derived from 3 years of research with the mobile social awareness system, nine design principles are proposed specifically for a mobile, ubiquitous social awareness application. The principles are: (1) support lightweight permissions, (2) assume reciprocity, (3) make it possible to appear differently to different people, (4) allow for commenting, modifying, and framing automatic disclosure, (5) provide for feedback, (6) allow the user to lie, (7) do not take control away from the user, (8) allow opportunistic use, and (9) do not try to do everything within the system.

2.4.5 Applications

Socially aware computing can be applied in various areas, such as public health, public safety, and urban planning. For example, through determining friendship based on sensory data, the public health organization can choose to inoculate friends of those randomly inoculated individuals, which has been proved to be efficient in controlling an epidemic outbreak (Cho 2009). Public safety involves the prevention of and protection from events that could endanger the public, such as crimes or disasters. Public video surveillance systems have greatly enhanced citywide event sensing and safety monitoring. With the gathered data, particularly data focused on the time, distribution, and geography of past events, the Los Angeles Police Department generates daily probability reports about when and where crimes are most likely to occur (Greengard 2012). MIT's Real Time Rome project (Calabrese and Ratti 2006) uses aggregated data from cell phones, buses, and taxis in Rome to better understand urban dynamics in real time. It offers support for intelligent transportation management. The Biketastic project (Reddy et al. 2010) improves bike commuting by collecting and mining data that bikers have contributed through their mobile phones. Bikers can then plan routes with the lowest probability of traffic accidents and the best air quality.

2.5 Socially Aware Computing Practice with Smartphones

2.5.1 Activity Recognition Based on Smartphones

We propose recognizing user activities based on a single tri-axial accelerometer in the smartphone. The smartphones are randomly put in the users' pant pockets without any limitations about the phone orientation.

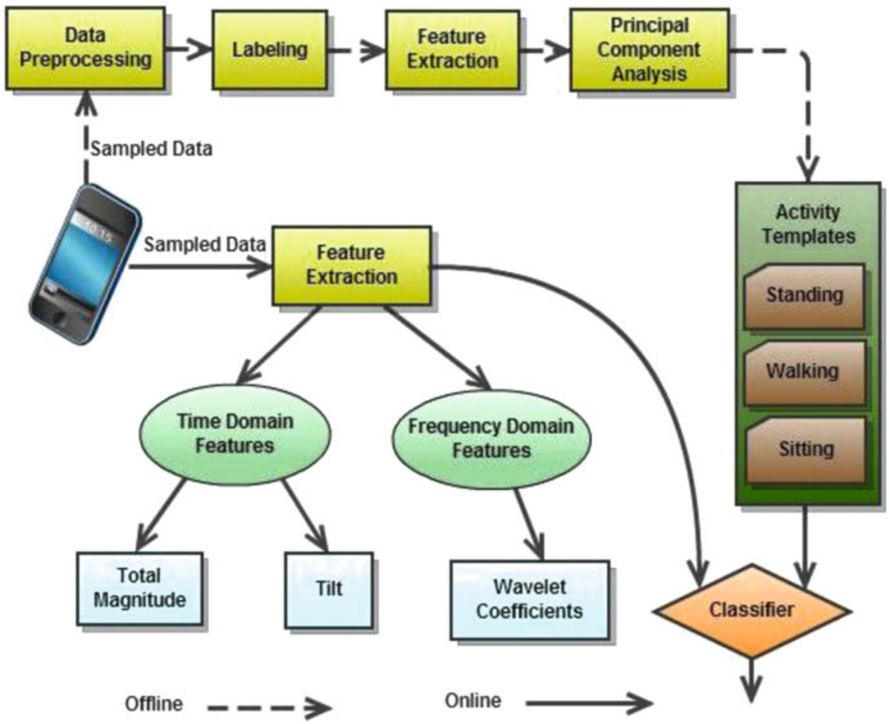

Fig. 2.2 Flow chart of activity recognition including offline learning and online classification

The activities targeted include two types: static activities (e.g., standing, sitting, lying, and driving) and repetitive activities (e.g., walking, running, ascending stairs, descending stairs, cycling, and jumping). Both time-domain features and frequency-domain features are investigated, such as mean of each axis, deviation of each axis, mean of total magnitude, deviation of total magnitude, tilt, linear regressive coefficients, and wavelet coefficients.

Figure 2.2 shows the framework of activity recognition consisting of two parts: the offline data training and the online classification. The offline data training part extracts features from the sampled data, and constructs templates for each activity. The online classification part extracts features of the sliding window, calculates the similarities between the target activity and templates, and selects a suitable class as the label of the sampled data in the sliding window.

The offline data training process consists of four steps. The data preprocessing step takes charge of data cleaning and data representation. Labeling defines the class of each sampled data using all the target activities. Feature extraction captures characteristics of each activity. To minimize the size of features involved, principal component analysis (PCA) is introduced to select the most discriminative features. Finally, a template will be generated for each activity, which describes the crucial feature parameters. To reduce time consumption, offline data training is performed

Table 2.1 Recognition rate

Activity	Percentage of records correctly recognized: Time-domain features (%)	Frequency-domain features (%)	Recognition rate (%)
Standing	98.98	1.02	98
Sitting	100	0	100
Lying (prone)	100	0	100
Lying (supine)	99.28	0.72	100
Driving	37.69	62.31	80
Walking	0	100	80
Running	56.76	43.24	86
Ascending	0	100	88
Descending	0	100	82
Cycling	97.50	2.50	84
Jumping	0	100	82
Average	53.66	46.34	89.1

on the PC or workstation. Only those results are transplanted onto the smart phone to serve as templates of user activities.

The online classification process extracts features and calculates similarities using activity templates. According to those similarities, the current inputs are classified into the corresponding type. To reduce computational complexity significantly, no low-pass filter is used. We design a lightweight, hierarchical recognition algorithm with adjusting step length. First, time-domain features are utilized to classify user activities based on template-based classification. However, it is difficult to discern some activities when only the time-domain features are taken into consideration. To discriminate the details of user activities, frequency-domain features are introduced. This algorithm adjusts the size of sliding window according to similarities to enhance recognition accuracy.

The recognition rate for each activity is presented in Table 2.1. The contributions of the time-domain and frequency-domain features are calculated. First, the average recognition rate reaches up to 89.1 %. The recognition rate demonstrates that activity recognition based on the low-resolution accelerometer with low sampling frequencies is feasible. Second, the majority of static activities are recognized in the first phase based on time-domain features. By contrast, most of the repetitive activities are discerned in the second phase based on the combined features. This demonstrates that those selected time-domain features are very useful in discriminating user activities, which favors a decrease in computational load. On one hand, opportunities resulting from the time-consuming frequency-domain feature extraction and the heavyweight decision tree algorithm are minimized. On the other hand, the introduction of classification based on combined features favors improvements in recognition rates, during which complex activities such as ascending and descending are discriminated based on combined features.

2.5.2 Enhancing Social Interaction with Smartphones

We build a service-oriented system architecture to support social interactions in campus-wide environments. The basic functions of the system consist of semantic extraction, pattern mining, ubiquitous search, and location management. The client side is running on smartphones, which collects contexts such as location, proximity, cell phone log, etc., and provides social services to the user for enhancing social interactions.

The server backend consists of several modules ranging from context aggregation, social network analysis, context storage, and knowledge mining to peer communication and admission control.

Generally speaking, campus life consists of study, communication, and entertainment. It is useful for people to learn about the usage of the facilities before planning. For example, *is the study lounge available? which classroom does my classmate sit in? is the tennis-court crowded?* Three applications were implemented and deployed based on the proposed architecture, which are closely related to daily campus life and aims to enhance the social interactions among college students.

The three applications are named *Where2Study, I-Sensing,* and *BlueShare* respectively. *Where2Study* aims to help users find a suitable place to study and locate his/her friends based on Wi-Fi positioning technology. *I-Sensing* is a campus information-sharing system based on participatory sensing, through which every user can publish his/her sensing requests and accomplish others' sensing tasks by using the sensors in their smartphones. *BlueShare* is a media-sharing application among Bluetooth devices based on the opportunistic network. The interesting media is sent to all users close to the Bluetooth devices. The advantage is the ability to transfer large files without any payments.

For space limitation, we here only show the details of the *Where2Study* application. Readers can refer to Yu et al. (2011) for more details about the applications. *Where2Study* not only presents the navigation map of a building to help students find classrooms (Fig. 2.3a), but also shows the status of all classrooms as shown in Fig. 2.3b, such as which classrooms are full and which ones have free seats. To check the detailed information of a particular room, a user can click a button in Fig. 2.3b and then the status of the seats in the room is displayed, as shown in Fig. 2.3c. Furthermore, the application supports querying the location and activity of user friends, as shown in Fig. 2.3d.

A key feature of this application is the capability to browse the status (e.g., name, location, and activity) of close friends. This allows users to reach out and be aware of their social network established by friendship, which will help each other to study (e.g., all my friends are studying at the moment). In addition, when a user encounters a problem during study, he or she could turn to their friends for discussion according to their location shown on the mobile phone.

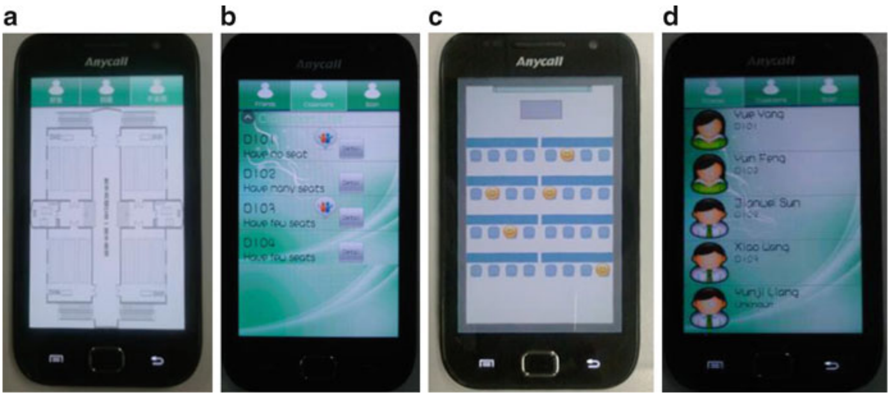

Fig. 2.3 Where2Study user interface: (**a**) map navigation, (**b**) rough status of all (**c**) detailed status of a particular classroom, and (**d**) friend location

2.5.3 Understanding Social Relationship with Mobile Phone Data

Investigating how a social group evolves is important for understanding its community dynamics and predicting its future structure.

We present a study of understanding social relationship evolution by using real-life anonymized mobile phone data. The data was captured by the MIT Reality Mining project (Eagle et al. 2009). An application running on the mobile phones continuously records user behaviors and communications such as location, proximate users, voice calls, and text messages. The collected data is anonymized in further analysis to protect user privacy.

We define a friendship as a directed relationship, i.e., person A regards another person B as his or her friend but not necessarily vice versa. The support vector machine (SVM) approach is adopted as the inference model to predict friendship based on a variety of features extracted from the mobile phone data, including proximity, outgoing calls, outgoing text messages, incoming calls, and incoming text messages. Second, we demonstrate the social relation evolution process by using the social balance theory. For the friendship prediction, we achieved an overall recognition rate of 97.0 % by number and a class average accuracy of 89.8 %. This shows that social relationships (not only reciprocal friends and non-friends, but non-reciprocal friends) can probably be predicted by using real-world sensing data. With respect to the evolution of friendship, we verified that the principles of reciprocity and transitivity play an important role in social relationship evolution.

2.6 Conclusion

This chapter presents the concepts and technologies of socially aware computing. The research paradigm has three features: sensing-based, data-driven, and field-study-based. Our current work in the field is described. Privacy is an important issue we need to consider. Sensing data captured in human daily lives, such as phone call and short message information, is highly sensitive. We need to balance between the benefit derived from the information and user privacy. Robust models and mechanisms are needed to safeguard user privacy during the sharing and usage of the sensing data. In the future, we also plan to apply the technologies in other applications, such as public health, urban transportation management, and environment monitoring.

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