Chapter 1
Human Sensors on the Move

Denzil Ferreira, Vassilis Kostakos, and Immanuel Schweizer

1.1 Human Sensors on the Move

In this section we provide an extensive summary of *human sensors on the move*, or mobile systems that are designed to collect data from smartphones that users carry in their everyday life. One can rely on people's own mobile phones to collect data as they are at their close vicinity 90 % of the time (Dey et al. 2011). These devices have immense potential to collect rich data about people's behaviour and habits, as well as their environment. In this chapter, we first outline the general idea of human sensor, then dive into some technical challenge before we present a number of systems to generate context on mobile phones.

1.2 Movement Generates Information

Mobility has received a lot of attention as a defining feature of the move from desktop-bound computing to pervasive computing. Strongly linked to mobility is the notion of encounter. The movement of people and devices through an urban environment brings them into contact with each other. In an urban pervasive computing system, there are additional patterns of encounter between diverse combinations of users, places, mobile devices, fixed devices, and services. This results in an

D. Ferreira (✉) • V. Kostakos
Center for Ubiquitous Computing, University of Oulu, Oulu, Finland
e-mail: denzil.ferreira@ee.oulu.fi; vassilis@ee.oulu.fi

I. Schweizer
Telecooperation Lab, Department of Computer Science, Technical University, Darmstadt, Germany
e-mail: schweizer@cs.tu-darmstadt.de

V. Loreto et al. (eds.), *Participatory Sensing, Opinions and Collective Awareness*, Understanding Complex Systems, DOI 10.1007/978-3-319-25658-0_1

enormously increased number of spontaneous interactions with consequent effects on security and privacy (Kindberg and Zhang 2003).

A number of projects have focused on capturing mobility data enabled by the popularisation of mobile and wireless technologies. For example, the Reality Mining project (Eagle and Pentland 2006) collected proximity, location and activity information, with proximity nodes being discovered through periodic Bluetooth scans and location information by cell tower IDs. Several other groups have performed similar studies. Most of these use Bluetooth to measure mobility (Balazinska and Castro 2003; Kostakos et al. 2010; Nicolai et al. 2006; Perttunen et al. 2014), while others rely on WiFi (Chaintreau et al. 2007; McNett and Voelker 2005). The duration of such studies varies from 2 days to over 100 days, and the numbers of participants vary from 8 to over 5000. The BikeNet project (Eisenman et al. 2010) explored the use of people-centric sensing with personal consumer-oriented sensing applications and sensor-enabled mobile phone applications, which can potentially enable applications such as noise mapping and pollution mapping. The Pervasive Mobile Environmental Sensor Grids (MESSAGE) project aimed to collect data at a metropolitan scale through smart phones carried by cyclists, cars, and pedestrians monitoring carbon dioxide values, with an ultimate goal of controlling traffic in the city of Cambridge. Similarly, the urban sensing project CENS (Burke et al. 2006) sought to develop cultural and technological approaches for using embedded and mobile sensing to invigorate public space and enhance civic life.

1.3 Smartphones as Information Gatekeepers

Mobile phones have become miniaturized computers that fit in a pocket. They are inherently *personal* and their potential to sense the user's environment, i.e., context, is appealing to researchers. The *convenience* and *availability* of mobile phones and *application stores* makes it easier for a researcher to reach *thousands* of users. More importantly, mobile phones have several built-in sensors (e.g., accelerometer, gyroscope). Primarily used to enhance the user experience, such as application functionality or mobile phone user interaction (e.g., vibration feedback, screen orientation detection), these sensors are increasingly being leveraged for research purposes.

For example, mobile phones have been used to understand population movement flows in a city (O'Neill et al. 2006), and the Reality Mining team led the way on user-focused data collection via mobile phones (Eagle and Pentland 2006). O'Neill et al. (2006) abstracted a city into a graph thus proposing a conceptual framework for designing and analysing pervasive systems for urban environments (Kostakos et al. 2006). This necessitates the ability to *detect*, *infer* and *predict* *individual* and *collective* users' needs. Paraphrasing Weiser (1999), the twenty-first century computer is a non-centralized, distributed computer amongst multiple devices, working together to sense the world. It is a computer that disappears and makes intelligent inferences about what its sensors capture and provides information when one needs it. Mobile phones are currently the most widespread sensing device. Widespread, mobile instrumentation promises research opportunities and facilitates a better understanding of human behaviour.

However, challenges inherent to mobile computing such as *heterogeneity*, *transparency*, *security*, to name only a few, require a *collaborative* research effort to manage user's context.

The next two sections are dedicated to the open challenges of *sensor calibration* and *energy consumption*. These challenges are inherent to all wireless sensor devices. But they are amplified by the scale of deployments and the mobility envisioned with smartphones.

1.4 Calibrating Smartphones

As highlighted last section, smartphones are the perfect sensing device. They provide powerful hardware, with new sensors built in with every hardware iteration. However, these sensors are cheap and generally of low quality. They are not built in to deliver high quality context on the move. Hence, a number of researchers have tackled the challenge of how to calibrate smartphones in the past. Calibration is a challenge most prevalent for physical sensors, e.g., the microphone. The microphone is a good example as it is often used by researchers to measure sound pressure levels. Combining these measurements creates powerful environmental maps. However, a smartphone microphone is meant to pick up voice, not measure sound pressure. There is no wind cancelation and some frequency are suppressed, while others are increased. This has led to a number of algorithms trying to calibrate smartphone microphones. Simple approaches use a constant (Rana et al. 2010), while more sophisticated algorithms alter the measured frequencies before applying a calibration constant (Schweizer et al. 2011; D'Hondt et al. 2013).

While these algorithms work, they require manual effort for every smartphone calibrated. This is infeasible as the number of smartphones in existence is growing rapidly. A more promising approach has been introduced by Hasenfratz et al. (2012). They propose on-the-fly calibration (Hasenfratz et al. 2012). Here, smartphones are calibrated while passing calibrated stationary sensors.

Mobility and scale seem to increase the calibration challenge with calibration. However, mobility creates possible contacts between sensors, hence, using the mobility of the users to calibrate the device seems to be the only feasible solution given the amount of devices in question. This is still a basic, open question to human sensors on the move, dictating the data quality of the overall system. Assuming we can generate calibrated samples, the next sections discusses the possible impact of sensing on the energy consumption and the user.

1.5 Energy Consumption

Capturing the user's context, especially in high fidelity as discussed last section or for real-time use cases, requires high sampling rates and continuous sensing. However, applications with high power consumption see only limited success (Banerjee et al. 2007). Smartphones are expected to last through at least one working day. Over the past years a lot of research has gone into understanding and measuring power consumption. Power consumption on smartphones may be derived by either directly measuring the power consumption (Schweizer et al. 2014) or using device dependent power models in combination with the system utilization (Zhang et al. 2010). Nacci et al. (2013) extend this approach by proposing a framework allowing automatic power model generation. These are then used to suggest the user certain energy conserving actions.

The increasing number and use of sensors make them a major source of power consumption in modern smartphones. However, it is only through the use of those sensors that mobile sensing is a worthwhile endeavour (Lane et al. 2010; Khan et al. 2013).

Considering the power drain, continuous sensing is incredibly hard to achieve. In recent efforts researchers have started to work on more energy-efficient continuous context sensing algorithms, e.g., for location (Zhuang et al. 2010; Kim et al. 2010) or activity (Wang et al. 2009). Others have focused on optimizing the network power consumption as the second largest consumer after the display (Rathnayake et al. 2012).

Based on this works, Kansal et al. (2013) analyse the trade-off between sensing accuracy and the power consumption of the smartphone. They argue that a programmer building mobile context sensing applications should be able to specify two dimensions: (1) the *latency* at which context change is detected and (2) the *accuracy* of the inferred context.

They propose the latency, accuracy, and battery (LAB) abstraction to specify these dimensions. Their Senergy API is then supposed to provide the most energy-efficient context sensing algorithm to fulfil the specified requirements. This is a powerful approach lending app developers a tool to improve both programmer productivity and energy efficiency.

Calibration and energy efficiencies are basic challenges in the sense that they limit data quality and quantity one can achieve with human sensing. They are also in some sense limitations imposed by the hardware used today. The next section tackles the crucial first step in building a research ecosystem for mobile sensing: addressing the challenge of *reusability* of context. Researchers and application developers need *tools* to detect, manage and *reuse* context, from diverse sources without starting from scratch.

1.6 Smartphone Instrumentation

Human sensing is changing rapidly. Hence, there is an increasing number of researchers building their own system, capturing and processing context. Given the basic challenges in capturing and processing context, e.g., calibration and energy, these systems often duplicate effort. Hence, reusability is crucial to decrease the barrier into human sensing and allow for much faster and, at the same time, higher quality in conducted research. Given this requirement, we will introduce 17 mobile context framework and highlight their audience, the sensors available, the system architecture, and their flexibility.

The Context Toolkit (Dey et al. 2001) is the reference conceptual framework for developing context-aware applications. It separates the *acquisition* and *representation* of context from the *use* of context by a context-aware application. Since the Context Toolkit was introduced, ubiquitous computing has become increasingly mobile and so has the user's context. To address different mobile computing constraints and challenges, several research tools have been developed over the years, as follows in chronological order.

CORTEX (Biegel and Cahill 2004) allows researchers to fuse data from mobile sensors, represent application context and reason about context. *CORTEX* introduced the concept of a sentient object model for the development of context-aware applications. By combining sentient objects and an event-based communication protocol for ad-hoc wireless environments, *CORTEX* targeted mobile context-aware researchers to define inputs and outputs, contexts, fusion services and rules using an inference engine which followed an event-condition-action (ECA) execution model. Similarly, *Context Studio* (Korpipää et al. 2004) is a middleware that takes into account users' mediation and accountability in context inference, as it is challenging to fully automate actions based on context alone. Mediation of context-dependent actions was manual, semi-automated, and fully automated. *Context Studio* uses a blackboard approach (i.e., multiple sub-problems combined solve the problem) to create contextual rules, actions and triggers. Users could combine the existing contextual probes to add context-awareness to the mobile phone.

ContextPhone (Raento et al. 2005) is a widget-based mobile middleware. ContextPhone is built on top of four essential components: sensors; communications; widgets and system services. Available sensors probed location, user interaction, communication behaviour and physical environment. Fundamental to *ContextPhone* was the idea of context as an understandable resource for the users, in other words, context intelligibility. Using widgets, users had control over the sensors data collection. *AWARENESS* (van Sinderen et al. 2006) is a middleware that prioritizes users' privacy concerns. The middleware applies the concept of Quality of Context (QoC) to express the quality characteristics of the context information. Users' privacy concerns would increase or decrease QoC, depending on how much context is shared at any given time (e.g., disabling GPS would reduce the QoC for the context of location). Context is shared with previously trusted devices and the mobile phone user is the sole controller of privacy aspects. *AWARENESS* focused on mobile healthcare applications for patients and medical researchers.

Momento (Carter et al. 2007) was a middleware with integrated support for situated evaluation of ubiquitous computing applications. Momento's mobile client displayed questions to the user and was able to log location, nearby people and audio. The researcher had a desktop client to configure and oversee a remote deployment. *Momento* was integrated with the Context Toolkit (Dey et al. 2001) for fixed applications. For researchers, *Momento* leveraged existing devices as much as possible; provided support for multiple communication options; supported qualitative, quantitative and context data in a unified client system; supported monitoring and notifications; and supported lengthy and remote studies. The *MyExperience* (Froehlich et al. 2007) middleware captured both sensor- and human-based data to understand the user's motivation, perception and satisfaction on mobile technology. Human-based data collection (e.g., surveys and user experience sampling) was triggered off sensor readings and pre-established researcher's rules. *MyExperience* supported remote opportunistic synchronization of the collected mobile data and survey answers to a remote server, to ensure access to the data as soon as possible.

CenceMe (Miluzzo et al. 2008) middleware inferred physical social context and shared information through social network applications (e.g., Facebook and MySpace). *CenceMe* introduces a split-level classification approach for sharing social context. Social context detected locally on the device is transferred to a backend server to match common shared social contexts to raise social awareness. With the split-level classification approach, classification can be done on the phone with the support of the backend servers, or entirely on the phone. CenceMe focused on users' social experiences. *EmotionSense* (Rachuri et al. 2010) focused on social psychology context. The middleware could sense individual emotions, activities, and verbal as well as proximity interactions amongst friends. The middleware could detect speakers' identities, emotions and location. EmotionSense supported social scientists, allowing them to describe sensing tasks and rules to manage sensors according to the detected users' social context.

Empath (Emotional Monitoring for PATHology) (Dickerson et al. 2011) was a middleware to remotely monitor emotional health for depressive illness. *Empath* is composed of a set of integrated wireless sensors, a touch screen station and mobile phones. Patients' diagnosis and therapeutic treatment planning were supported by reports generated by aggregating context such as sleep, weight, activities of daily living, and speech prosody. The behaviour analysis routines run on the server and results would be displayed on the touch screen fixed station at patients' homes.

Funf (Friends and Family) (Aharony et al. 2011) middleware focused on social and behaviour sensing. Funf instruments the available hardware and software sensors on mobile phones (e.g., GPS, accelerometer, calls, messages, installed applications, running applications). Funf is for researchers interested in collecting social and behavioural data and studies. "Self-tracking" users can also use the Funf Journal application to collect their personal mobile data. *Ginger.io* (Ginger.io 2012) is a behavioural analytics middleware that turns mobile data into health insights. *Ginger.io* provides a web-based dashboard for healthcare researchers and providers and a mobile application for patients. The mobile application passively collects movement, call and texting patterns. In a daily or weekly basis, the mobile application requests feedback from the patients, as 3–5 steps questionnaires.

SystemSens (Falaki et al. 2011) middleware captures *usage context* of mobile phones. Usage context is the collection of users' interactions with research applications. The users' interactions include battery, call, CPU usage, cell location, data connection active and traffic and telephony information events. SystemSens is a researchers' middleware to instrument research applications and loggers. *Ohmage* (Ramanathan et al. 2012) is a mobile phone-to-web middleware designed to create and manage experience sampling based data collection campaigns in support of mobile health pilot studies. It supports time- and location-triggered self-reports; activity recognition based on sensor-fusion of accelerometer, GPS, Wi-Fi and cell tower radios; location tracking; exercise and sleep tracking; acoustic traces for social interaction detection; motivational messages for participant engagement. *ODK* (Open Data Kit) *Sensors* (Brunette et al. 2012) is a middleware to simplify the interface between external sensors and mobile phones. *ODK Sensors* abstracts application and driver development from user applications and device drivers, by management of discovery, communication channels and data buffers. It is component-based, allowing developers to focus on writing minimal pieces of sensor-specific code, enabling an ecosystem of reusable sensor drivers. Integration of new sensors into applications is possible by downloading new sensor capabilities from an application market, without modifications to the operating system.

DeviceAnalyzer (Wagner et al. 2014) is a framework capturing the most comprehensive set of raw sensor data. While no additional processing is done, the application has been used to collect the largest, most detailed dataset of Android phone use publicly available to date.

Kraken.me (Schweizer et al. 2014) is a toolkit for users providing extensive sensing capabilities for mobile, online, and desktop context. By integrating hardware, software, and human sensors across device boundaries, Kraken.me provides comprehensive information to the user. The user can access that information through an online portal at http://www.kraken.me and other apps can make use of this data to provide context sensitive-services.

AWARE (Ferreira 2013) is an instrumentation toolkit for researchers of context-aware mobile computing, application developers and users. Using AWARE, raw data sensed from hardware, software and human sensors is converted to units of information (i.e., mobile context) that can be shared between other applications, sensors and humans alike. AWARE provides a foundation to create new mobile research tools for data mining and visualization. AWARE takes into account the wide range of interrelated sources of context information and the relationships amongst them, including the user's individual and social behaviour. AWARE is available at http://www.awareframework.com.

Table 1.1 summarizes the reviewed tools for mobile context-aware research. For each middleware the table highlights the potential audience (researchers, developers, users) and its sensing capabilities (hardware sensors, software sensors, humans). The table also distinguishes between two types of management: centralized (i.e.,

Table 1.1 Summary of mobile phone middleware for sensing data

	Audience			Sensing			Architecture		Context		
Middleware	R	D	U	HW	SW	U	Centralized	Distributed	Shared	Dynamic	Scalable
CORTEX	x			x	x		x		x		x
ContextStudio			x	x	x	x	x		x	x	
ContextPhone	x		x	x	x	x		x	x		
AWARENESS	x			x	x			x	x	x	
Momento	x			x	x	x		x		x	
MyExperience	x			x	x	x		x			
CenceMe			x	x	x			x		x	
EmotionSense	x			x	x		x			x	
Empath	x		x	x	x			x			x
Funf	x		x	x	x		x		x		x
Ginger.io	x		x	x	x	x		x	x		
SystemSens	x			x	x			x			x
Ohmage	x		x	x	x	x	x		x		
ODK Sensors		x		x				x	x	x	x
DeviceAnalyzer	x		x	x	x	x	x		x		x
Kraken.me			x	x	x	x	x		x		x
AWARE	x	x	x	x	x	x	x	x	x	x	x

R researcher, *D* developer, *U* user, *HW* hardware, *SW* software

on the phone itself) or decentralized (distributed among many devices). Finally, the table includes further *properties* of context such as *shared*, *dynamic* and *scalable* context (Dey et al. 2001). Shared context can be used locally on the mobile phone for other applications or devices; dynamic context can be extended in runtime and adapts the current context; and scalable middleware supports adding new sources of context beyond core contextual sources. S*hared* context is required for *multidisciplinary research* and *collaboration*, and provides *reusability*, *delegation*, and *accessibility* (e.g., *security*, *privacy*, *online visualization*) of context. *Dynamic* context supports mobile context *volatility*, such as *runtime adaptation* and *manipulation* (i.e., *reflection*, *frequency*). Lastly, *scalable* context provides support for context *heterogeneity*, *transparency*, *redundancy* and *portability*.

Making the transition from mobile phones to "smartphones", in the true sense of the word, requires more tools that offer programming and development support. The development of "contextaware" applications remains challenging because researchers have to deal with obtaining raw sensor data, analyzing the data to produce context, and often writing code from scratch that require years of expertise to acquire. There is a lack of a *coherent* and *modular* repository of relevant tools. Research fragmentation is the *biggest* challenge for this field.

1.7 Summary

Obviously, researchers are fascinated by the prospect of *human sensors on the move*. We first discussed mobility and the versatility of smartphones as the two main properties responsible for this fascination. We then shortly discussed calibration and energy consumption as two examples of basic, open challenges every system that captures sensor data on the move faces. Lastly, we introduced 17 mobile context frameworks build to capture, process and analyse data.

The sheer number of systems available goes to highlight one of the core challenges for the future of human sensing. Trying to promote an open ecosystem of reusable tools to get new researchers and developers to build betters systems quickly and focus on understanding humans, i.e., their activity, goals and intentions, rather than solving technical challenges.

References

Aharony, N., Pan, W., Ip, C., Khayal, I., Pentland, A.: The social fMRI: measuring, understanding, and designing social mechanisms in the real world. In: UbiComp '11: Proceedings of the 13th International Conference on Ubiquitous Computing, pp. 445–454. ACM (2011). doi:10.1145/2030112.2030171

Balazinska, M., Castro, P.: Characterizing mobility and network usage in a corporate wireless local-area network. In: MobiSys '03: MobiSys, pp. 303–316. ACM (2003). doi:10.1145/1066116.1066127

Banerjee, N., Rahmati, A., Corner, M.D., Rollins, S., Zhong, L.: Users and batteries: interactions and adaptive energy management in mobile systems. In: UbiComp '07: Proceedings of the 9th International Conference on Ubiquitous Computing, pp. 217–234. Springer, Berlin/Heidelberg (2007)

Biegel, G., Cahill, V.: A framework for developing mobile, context-aware applications. In: PerCom, pp. 361–365. IEEE (2004). doi:10.1109/PERCOM.2004.1276875

Brunette, W., Sodt, R., Chaudhri, R., Goel, M., Falcone, M., Van Orden, J., Borriello, G.: Open data kit sensors: a sensor integration framework for android at the application-level. In: MobiSys '12: Proceedings of Mobisys, pp. 351–364. ACM (2012). doi:10.1145/2307636.2307669

Burke, J.A., Estrin, D., Hansen, M., Parker, A., Ramanathan, N., Reddy, S., Srivastava, M.B.: Participatory sensing. In: First Workshop on World-Sensor-Web: Mobile Device Centric Sensory Networks and Applications at Sensys '06 (2006)

Carter, S., Mankoff, J., Heer, J.: Momento: support for situated ubicomp experimentation. In: CHI '07: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 125–134. ACM (2007). doi:10.1145/1240624.1240644

Chaintreau, A., Hui, P., Crowcroft, J., Diot, C., Gass, R., Scott, J.: Impact of human mobility on opportunistic forwarding algorithms. IEEE Trans. Mob. Comput. **6**(6), 606–620 (2007). doi:10.1109/TMC.2007.1060

D'Hondt, E., Stevens, M., Jacobs, A.: Participatory noise mapping works! An evaluation of participatory sensing as an alternative to standard techniques for environmental monitoring. Pervasive Mob. Comput. **9**(5), 681–694 (2013)

Dey, A.K., Abowd, G.D., Salber, D.: A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications. Hum. Comput. Interact. **16**(2), 97–166 (2001). doi:10.1207/S15327051HCI16234_02

Dey, A.K., Wac, K., Ferreira, D., Tassini, K., Hong, J.-H., Ramos, J.: Getting closer: an empirical investigation of the proximity of user to their smart phones. In: UbiComp '11: Ubicomp, pp. 163–172. ACM (2011). doi:10.1145/2030112.2030135

Dickerson, R.F., Gorlin, E.I., Stankovic, J.A.: Empath: a continuous remote emotional health monitoring system for depressive illness. In: WH '11: Proceedings of the 2nd Conference on Wireless Health, pp. 5:1–5:10. ACM (2011). doi:10.1145/2077546.2077552

Eagle, N., Pentland, A.: Reality mining: sensing complex social systems. Pers. Ubiquit. Comput. **10**(4), 255–268 (2006). doi:10.1007/s00779-005-0046-3

Eisenman, S.B., Miluzzo, E., Lane, N.D., Peterson, R.A., Ahn, G.-S., Campbell, A.T.: BikeNet: a mobile sensing system for cyclist experience mapping. ACM Trans. Sen. Netw **6**(1), 6:1–6:39 (2010). doi:10.1145/1653760.1653766

Falaki, H., Mahajan, R., Estrin, D.: SystemSens: a tool for monitoring usage in smartphone research deployments. In MobiArch '11: Proceedings of the Sixth International Workshop on Mobiarch, pp. 25–30. ACM (2011). doi:10.1145/1999916.1999923

Ferreira, D.: Aware: a mobile context instrumentation middleware to collaboratively understand human behavior. Doctoral Dissertation, University of Oulu (2013)

Froehlich, J., Chen, M.Y., Consolvo, S., Harrison, B., Landay, J.A.: MyExperience: a system for in situ tracing and capturing of user feedback on mobile phones. In: MobiSys '07: Proceedings of the 5th International Conference on Mobile Systems, Applications and Services, pp. 57–70. ACM (2007). doi:10.1145/1247660.1247670

Ginger.io: Ginger.Io. [Web page] Retrieved from http://ginger.io/ (2012)

Hasenfratz, D., Saukh, O., Sturzenegger, S., Thiele, L.: Participatory air pollution monitoring using smartphones. In: 2nd International Workshop on Mobile Sensing. ACM (2012)

Kansal, A., Saponas, S., Brush, A.J., McKinley, K.S., Mytkowicz, T., Ziola, R.: The latency, accuracy, and battery (LAB) abstraction: programmer productivity and energy efficiency for continuous mobile context sensing. ACM SIGPLAN Not. **48**(10), 661–676 (2013)

Khan, W.Z., Xiang, Y., Aalsalem, M.Y., Arshad, Q.: Mobile phone sensing systems: a survey. IEEE Commun. Surv. Tutorials **15**(1), 402–427 (2013)

Kim, D.H., Kim, Y., Estrin, D., Srivastava, M.B.: SensLoc: sensing everyday places and paths using less energy. In: Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems, pp. 43–56. ACM (2010)

Kindberg, T., Zhang, K.: Secure spontaneous device association. In: UbiComp 2003: Ubiquitous Computing, pp. 124–131. Springer, Berlin/Heidelberg (2003). doi:10.1007/978-3-540-39653-6_9

Korpipää, P., Häkkilä, J., Kela, J., Ronkainen, S., Känsälä, I.: Utilising context ontology in mobile device application personalisation. In: MUM '04: Proceedings of the 3rd International Conference on Mobile and Ubiquitous Multimedia, pp. 133–140. ACM (2004). doi:10.1145/1052380.1052399

Kostakos, V., O'Neill, E., Penn, A.: Designing urban pervasive systems. Computer **39**(9), 52–59 (2006). doi:10.1109/MC.2006.303

Kostakos, V., O'Neill, E., Penn, A., Roussos, G., Papadongonas, D.: Brief encounters: sensing, modeling and visualizing urban mobility and copresence networks. ACM TOCHI **17**(1), 2 (2010). doi:10.1145/1721831.1721833

Lane, N.D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., Campbell, A.T.: A survey of mobile phone sensing. IEEE Commun. Mag. **48**(9), 140–150 (2010)

McNett, M., Voelker, G.M.: Access and mobility of wireless PDA users. Mob. Comput. Commun. Rev. **9**(2), 40–55 (2005). doi:10.1145/1072989.1072995

Miluzzo, E., Lane, N.D., Fodor, K., Peterson, R., Lu, H., Musolesi, M., … Campbell, A.T.: Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application. In: SenSys '08: Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems, pp. 337–350. ACM (2008). doi:10.1145/1460412.1460445

Nacci, A.A., Trovò, F., Maggi, F., Ferroni, M., Cazzola, A., Sciuto, D., Santambrogio, M.D.: Adaptive and flexible smartphone power modeling. Mob. Netw. Appl. **18**(5), 600–609 (2013)

Nicolai, T., Yoneki, E., Behrens, N., Kenn, H.: Exploring social context with the wireless rope. In: OTM, pp. 874–883 (2006). doi:10.1007/11915034_112

O'Neill, E., Kostakos, V., Kindberg, T., Schiek, A., Penn, A., Fraser, D., Jones, T.: Instrumenting the city: developing methods for observing and understanding the digital cityscape. In: Ubicomp, pp. 315–332. Springer (2006). doi:10.1007/11853565_19

Perttunen, M., Kostakos, V., Riekki, J., Ojala, T.: Spatio-temporal patterns link your digital identities. Comput. Environ. Urban Syst., 1–10 (2014). doi:10.1016/j.compenvurbsys.2013.12.004

Rachuri, K.K., Musolesi, M., Mascolo, C., Rentfrow, P.J., Longworth, C., Aucinas, A.: EmotionSense: a mobile phones based adaptive platform for experimental social psychology research. In: Ubicomp '10: Proceedings of the 12th ACM International Conference on Ubiquitous Computing, pp. 281–290. ACM (2010). doi:10.1145/1864349.1864393

Raento, M., Oulasvirta, A., Petit, R., Toivonen, H.: ContextPhone: a prototyping platform for context-aware mobile applications. IEEE Pervasive Comput. **4**(2), 51–59 (2005). doi:10.1109/MPRV.2005.29

Ramanathan, N., Alquaddoomi, F., Falaki, H., George, D., Hsieh, C., Jenkins, J., Estrin, D.: Ohmage: an open mobile system for activity and experience sampling. In: PervasiveHealth, pp. 203–204. IEEE (2012)

Rana, R.K., Chou, C.T., Kanhere, S.S., Bulusu, N., Hu, W.: Ear-phone: an end-to-end participatory urban noise mapping system. In: Proceedings of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks, pp. 105–116. ACM (2010)

Rathnayake, U., Petander, H., Ott, M., Seneviratne, A.: EMUNE: architecture for mobile data transfer scheduling with network availability predictions. Mob. Netw. Appl. **17**(2), 216–233 (2012)

Schweizer, I., Bärtl, R., Schulz, A., Probst, F., Mühläuser, M.: NoiseMap-real-time participatory noise maps. In: Proceedings of the 2nd International Workshop on Sensing Applications on Mobile Phones (PhoneSense'11), pp. 1–5 (2011)

Schweizer, I., Bärtl, R., Schmidt, B., Kaup, F., Mühlhäuser, M.: Kraken.me mobile: the energy footprint of mobile tracking. In: Proceedings of the 6th International Conference on Mobile Computing, Applications and Services (MobiCASE), pp. 82–89. IEEE (2014)

van Sinderen, M.J., van Halteren, A.T., Wegdam, M., Meeuwissen, H.B., Eertink, E.H.: Supporting context-aware mobile applications: an infrastructure approach. IEEE Commun. Mag. **44**(9), 96–104 (2006). doi:10.1109/MCOM.2006.1705985

Wagner, D.T., Rice, A., Beresford, A.R.: Device analyzer: understanding smartphone usage. In: Mobile and Ubiquitous Systems: Computing, Networking, and Services, pp. 195–208. Springer (2014)

Wang, Y., Lin, J., Annavaram, M., Jacobson, Q.A., Hong, J., Krishnamachari, B., Sadeh, N.: A framework of energy efficient mobile sensing for automatic user state recognition. In: Proceedings of the 7th International Conference on Mobile Systems, Applications, and Services, pp. 179–192. ACM (2009)

Weiser, M.: The computer for the 21st century. ACM SIGMOBILE Mob. Comput. Commun. Rev. **3**(3), 3–11 (1999). doi:10.1145/329124.329126

Zhang, L., Tiwana, B., Qian, Z., Wang, Z., Dick, R.P., Mao, Z.M., Yang, L.: Accurate online power estimation and automatic battery behavior based power model generation for smartphones. In: Proceedings of the Eighth IEEE/ACM/IFIP International Conference on Hardware/Software Codesign and System Synthesis, pp. 105–114. ACM (2010)

Zhuang, Z., Kim, K.H., Singh, J.P.: Improving energy efficiency of location sensing on smartphones. In: Proceedings of the 8th International Conference on Mobile Systems, Applications, and Services, pp. 315–330. ACM (2010)