A Research Framework for the Smartphone-Based Contextual Study of Mobile Knowledge Work

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Abstract. We present an initial research framework for the contextual study of mobile knowledge work that combines automatic, objective data collection from smartphone sensors with subjective participant self-reported data possibly complemented with researcher conducted interviews. The framework shows how raw sensor data, contextual information inferred from the sensor data, both in real-time and post hoc, can be used in tandem with smartphone administered questionnaires and post hoc in-depth interviews to study mobile knowledge work. We evaluate the framework by reporting some early experiences from a pilot study of mobile knowledge work.

Keywords: mobile sensing, mobile data collection, mobile knowledge work, context-awareness, smartphone-based research.

1 Introduction

The everyday activities and work of many knowledge workers and other professionals increasingly take place in a turbulent national and international environment. Rather than following a regular and well-defined path, the professionals have to go through numerous transitions across job descriptions, positions, and moving from one workplace or enterprise to another. New groups of professionals are emerging who are doing mobile and multi-locational work; a knowledge-intensive activity that involves the use of sophisticated information and communication technologies (ICTs) at various places (at workplace, in transition, at places provided by customers, at public places and at home) during a day or week. Professionals who pursue such demanding mobile knowledge work often also function and work in a complex social

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context under severe time constraints. These characteristics affect the work itself, its flow, and the experienced stressfulness and wellbeing at work.

Everyday activities of knowledge workers in general, and mobile workers in particular, take place at boundaries between work, family, and recreational activities. The activities, or their effects on wellbeing, cannot be properly investigated by relying on traditional methods of location-fixed participant observation (ethnography). Shadowing their activities across contexts would not be practical. Yet, in order to have a thorough view of a professional's daily life, it is important to trace his or her activity in its authentic contexts that are often heterogeneous, partially unpredictable, and changeable in nature. Questionnaires, retrospective interviews, and laboratory experiments are valuable, but they often fail to capture real actions of real people in real life. When asked about their behavior, people are prone to give responses biased towards overestimating their positive traits and underestimating the negative or responses that are socially desirable. To overcome these challenges novel research methods and tools for tracing professional activity are needed. However, the same technical developments that have led to the emergence of mobile knowledge work have also opened up promising opportunities for research method and tool development.

The current smartphones are powerful, programmable computing devices. They are embedded with a plethora of sensors that can automatically and unobtrusively collect a lot of rich information about the device usage and its immediate surroundings. Smartphones can be used both to administer and answer survey questionnaires on the move, in situ. Given their global popularity and the relative ease of distributing research applications it is possible to reach even global scale sample sizes. The rich capabilities that smartphones and their sensors have for the data collection and study of varied phenomena has been noted recently [1-5]. Their potential in different kinds of social and behavioral research has been addressed by several investigators [6-10].

In computer science and engineering, context-aware computing, i.e., computational systems that are aware -or sense- the setting and environment they are used and adapt to those conditions, has been a hot topic for at least a decade. A widely cited definition for context is the following [11]: "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application including the user and the application themselves." Both the technical capabilities for collecting sensor data about contexts and the algorithms to infer specific semantic contexts from the sensor data are developing rapidly and becoming available even on the commercial smartphone operating systems. For researchers interested in human behavior, context-awareness enables automatic data collection about the context of the device and its user. If the context can be inferred immediately, the information could be used to launch context-specific questionnaires [12]. This allows contextual sampling of experiences and events of people's daily life. Automatically collected data from smartphones can complement and validate self-reported data and to support more in-depth interviews. These tools and technologies seem particularly useful for the study of mobile knowledge work but can also be useful for the study of a wide range of other phenomena, especially in studying the daily life and experiences of people.

In this paper we present a smartphone-based research framework for the contextual study of mobile knowledge work that combines automatic, unobtrusive, and objective data collection from smartphone sensors with subjective participant self-reported data possibly complemented with researcher conducted interviews. The research framework shows how raw sensor data, contextual information inferred from the sensor data, both in real-time and post hoc, can be used in tandem with smartphone administered (context-specific and/or context-agnostic) questionnaires and in-depth interviews to study mobile knowledge work. We evaluate the framework by reporting experiences from a small pilot study of a group of mobile knowledge workers.

The rest of the paper is structured as follows. Next, we describe mobile sensing of contexts. In section 3 we present the research framework which we then demonstrate and evaluate in section 4. Discussion and our conclusions end the paper.

2 Mobile Sensing of Contexts

For many their personal smartphone is their most important communication and computational device. They use it throughout the day, every day, and carry it wherever they go. The smartphones are often equipped with many sensors like GPS, accelerometer, gyroscope, camera, microphone, magnetic field, ambient light, and temperature. As smartphones are programmable, device interaction and data contents can be 'sensed' as well. These could include running applications, screen orientation, cell tower ID, call and SMS logs, contacts and calendar entries, to name a few.

While useful for many purposes, the raw sensor data as such is considerably less useful for the study of mobile knowledge work. In most cases, the raw sensor data needs to be interpreted as human behavior (e.g., walking, sitting, talking) or as a particular, meaningful context of the person (e.g., being at home, at work, at a cafe, in a bus, or a noise level of environment) to be useful, although the raw data could be used to validate some of participants' self-report or interview data. An expanding amount of research is being directed to the development of software tools and algorithms for using sensor data to automatically recognize activities and contexts [2-3].

The development of context recognition algorithms and their implementation on the phones is a challenge. Combined with possibly multimodal data collection from the phone sensors, the potentially computationally complex context inference algorithms can be energy hungry. This is a challenge because of the limited battery power of smartphones. This can be partially solved by offloading all or some of the inference algorithm computation to the cloud if a network connection is available. However, this also consumes energy and might hike up data costs for the participant. Moreover, from the research point of view, one of the main challenges in smart phone data collection is the need to transmit data via networking to servers. Although global Internet is growing, in large parts of the globe the access to networks is still meagre and require stand-alone devices for data collection.

Many of the algorithms require 'training data', i.e., data labeled by the user to correspond to a certain physical activity (such as walking) or context (such as being in a bus). Any mobile sensing research tool probably needs to enable training of sensing algorithms by categorizing and labeling activities. Individual differences and the myriad situations where activities and contexts occur mean they can become blurred (e.g., standing in a bus). This makes the reliable algorithm development challenging.

Table 1. Mobile knowledge work context framework (adapted from [4])

	Personal			**Environmental**		
	End user	**Social Environment**	**Activity/ Task**	**Conditions**	**Infrastructure**	**Location**
Profiled	Identity Age (Questionnaires)	Contacts Social network Organization	Calendar entries (like gym, meeting)	User taken photos (conditions visible?)	Devices Operating systems	Tagged places Calendar entries
Sensed	Talk patterns Biofeedback from connected external sensors (heart rate, blood pressure)	Surrounding devices Voices Phone contacts	Calling Talking Messaging Using apps	Temperature Noise level Ambient light	Battery level Signal strength Access alternatives	GPS coordinates Cell id Altitude Velocity
Derived	At sleep/awake Health condition Stress level	Surrounding people Co-location Alone Meeting	Sitting Standing Walking	Weather Day/night Season	Network quality Device operating range	Semantic place (e.g., home, office) Transport
Time (all of the above, their state and changes, can be described as a snapshot in time or a period of time) Day of week, weekend, time of day, etc.						

Nevertheless, many activities and contexts can be identified continuously, or post hoc, from the collected sensor data, either automatically or with some categorized training data. Some of higher-level activity and context detection functionality is becoming available on commercial smartphone platforms in the form of APIs (application programming interface). For example, as of Google I/O developer conference 2013, Android's Google Play Services Location API includes functionality for instant and continuous activity recognition (whether the phone is still, walking, cycling, or in-vehicle) and also for setting up geofences (i.e., geographic boundaries around some interesting location) and then receiving notifications when the phone crosses the geofence. This could, for example, be used to follow how much time a person spends at home or at the office. Although smartphone platforms will surely provide more such context-awareness functionality in the future, it is probable that they will cover only a subset of activity and needs and possibilities of context identification interesting for the study of mobile knowledge work.

Context is a multifaceted concept and can refer to many a thing. Soikkeli et al. [4] provide a useful framework to categorize contexts that is geared to handset-based data sources. The framework divides contexts into the broad categories of Personal and

Environmental. Personal contexts are further categorized as End User, Social Environment, and Activity/Task while Environmental contexts are divided into categories of Conditions in the immediate physical environment of the person, Infrastructure i.e., computational infrastructure available for the user, and Location i.e., not just the point on a map. In addition to Personal and Environmental the framework includes Time as the third broad category. Researchers might be interested in a snapshot of contexts in time or over a time period. The sensor data collected from smartphones typically has a timestamp attached to each data point. The researchers might analyze the past (context history), the present (current context), or the future (predicted context). The framework also adds a categorization dimension for contexts according to the data source used to determine the context. The data sources are: Profiled, i.e., user self-reported data, which could include labeling data discussed above, research questionnaire answers, and any information inputted by the user otherwise like e.g., phone calendar entries; Sensed, i.e., direct automatic sensor measurements; and Derived, i.e., context inferred via algorithms or otherwise based on Sensed and/or Profiled data.

Table 1 presents a context framework for mobile knowledge work (adapted from [4]) with some relevant context examples in each category. Examples in the Derived category also show what kind of contexts can currently be inferred based on smartphone sensor raw data. However, to the best of our knowledge there currently are no research toolsets that would have recognition algorithms for all of these.

3 A Research Framework for Contextual Study of Mobile Knowledge Work

3.1 Overview

In this section we present a smartphone-based research framework for contextual study of mobile knowledge work that combines mobile sensing and user self-report questionnaires with possible in-depth interviews. Depending on the research objectives, the framework can be adapted to include multiple combinations of contexts studied, data sources and sampling strategies used, and study lengths. We also discuss requirements for tool support but do take a future-oriented view in anticipating rapid progress in research tools that include an expanding range of automatic context-sensing functionality. We assume the toolset enables researchers to collect information about the contexts of a knowledge worker over time automatically (via sensing) and via user input (profiled) which also could be used to train the algorithms to identify contexts automatically. The toolset should also enable researchers administer traditional survey questionnaires via the smartphone.

3.2 Research Design Issues

When designing smartphone based contextual research, several issues need to be considered carefully as there are several tradeoffs involved related to the smartphone energy consumption, privacy, the burden placed on participants, and the amount of data generated vis-a-vis the research needs, data sources, and sampling rates used. If poorly designed, it can lead to participants dropping out of the study and to a poor quality data. We will discuss some of these issues below.

Energy Consumption and Smartphone-Based Sensing. Any measurement taken from the phone will consume its battery. However, some sensors are more energy hungry than others. These problems are highlighted because the research applications are likely to be installed on the participants' personal or work phones instead of an additional research device. The participants will surely be annoyed if the research application consumes so much battery power that it interferes with their normal phone usage. The research design should take energy consumption into account when deciding the sensors and the sampling rates used. For many purposes, continuous sensing is not necessary. Energy consumption can also be driven higher if there is a need to upload data to a cloud server.

Privacy. When the research is done on the participants' personal phones protecting their privacy is critical. Data transfer and storage must be secure. The participants must be made aware of what data is collected, what it will and can be used for as the possibility to infer contextual information from raw sensor data is not obvious to a layperson, how long it is stored for, etc. Another privacy problem is that smartphone data collection may indirectly collect information about other people who have not given their informed consent.

Burden on Participants. Automatic data collection from sensors does not put any additional burden on the participants directly but is does consume battery power. The participants may need to charge their phone more frequently than they are used to or is convenient for them.

Naturally, any data collection that requires user input burdens the participants. Training data collection for context detection algorithms in the beginning of a study is largely unavoidable as the data is necessary for the algorithms to function properly. The burden from the manual inputting of contexts or activities can be balanced by limiting the number of contexts or activities logged.

Answering research questionnaires is the more burdensome the more often the participant needs to answer them. A balance must be struck between sampling frequency and questionnaire length. If the sampling is based on detected contexts or activities the participant might be prompted to answer the questionnaire in very quick succession, which could be irritating especially if the questionnaire is long. The research toolset should limit how often the participant has to answer a questionnaire within a timeframe and how soon the participant needs to answer the questionnaire again.

Amount of Data Collected. Mobile sensing can yield a surprisingly large volume of data. This causes a few challenges for the research design. First, the local data storage on a smartphone has its limits. In a longer study it might be filled – to the undoubted irritation of the participant – and subsequent data lost if the collected data is not transferred elsewhere from the device in a planned manner. Second, the continuous data transfer adds also drains the battery. And third, if data transfer is done over a mobile network, it might cause a huge phone bill for the participant (or the research project). To avoid this, the data transfer should be done over WLAN connection. In smaller studies, manual data transfer via physical data cables can be feasible.

Participant Sample Sizes and Data Collection Methods. The smartphone-based contextual study allows mixed-method research designs combining mobile sensing, questionnaires, and interviews [15]. Automatic sensing is the least labor-intensive data collection method and could therefore include the whole group of participants. As collecting self-report data, whether context-labeling or questionnaire answers, is burdensome for the participants and the analysis of the data more resource-consuming for the researchers, self-reported data could be collected from a smaller subset of participants. The subset could be selected randomly or purposefully based on mobile sensing data or some background information. Further, as interviewing is more resource consuming than answering smartphone questionnaires, the sample for any interviews could again be smaller and chosen randomly or based on background information and mobile sensing and/or questionnaire data.

3.3 Research and Data Collection Phases

Next, we will discuss the different phases of the data collection in their chronological order. A study following the framework might not include all of the phases.

Installing the Research Application on Participants' Smartphones. First, the research application including the mobile sensing and questionnaire functionality must be installed on the participants' smartphones. If the participants are known, the application or a link to download the application can be sent to them directly. If the participants are unknown, the link to download the application can be distributed on the web or the application can be included in the mobile application stores like Google Play or Apple AppStore.

Pre-Study Survey. A pre-study survey could include questions on demographics and other background information. Further, it could include items and measures that can be used in pre- and post-test (or before-after) type of analysis. Answering the survey could be required before other data collection would begin.

Training Period for Labeling Data for Learning Algorithms. A period of collecting labeled training data for context inference learning algorithms is required. Depending on the research objectives, the more comprehensive data collection might begin simultaneously or after this phase.

Data Collection. This phase can combine automatic sensing, and participant self-reporting via questionnaires and categorization of contexts.

Post-Study Survey. A post-study survey done after the data collection period would support before/after type of analysis.

Interviews. As discussed earlier, mobile sensing and questionnaire data could be supported with in-depth retrospective qualitative interviews with a subset of participants. The interview could be supported by an initial analysis mobile sensing and questionnaire data of the participant. Continuously sensed data about the contexts, activities, and locations of the participant during the research could provide a useful memory anchor for the interview or for user diaries following the Day Reconstruction Method [13] or the method of stimulated recall.

Analysis of Data and Results. Naturally, data analysis is the last phase. This phase can include deriving interesting information, like contexts and activities, from the collected raw sensor data.

4 Pilot Study Experiences

4.1 Overview and Toolset

We conducted a pilot study following the research framework to study mobile knowledge work of a sample of 8 academic professionals during one work week, i.e., five consecutive working days but not necessarily from Monday to Friday. The toolset we used included two research applications that have been developed separately: Contextual Activity Sampling System (CASS-Q) for self-report questionnaires and ContextLogger3 for collecting sensor data and context and activity labeling.

The CASS-Q system was originally developed as a Java application for Symbian phones [14] but the current version of the CASS-Q client[1] runs on the Android operating system. The questionnaires are created on the management system which runs as a cloud service. The questionnaires can include a wide range of questions like open ended and multiple-choice questions, questions with different numerical scales, e.g., Likert, and recording audio answers or taking photographs.

ContextLogger3[2] [15] is a research application running on Android that allows researchers to collect smartphone sensor data on the background and participants to self-report context and activity labeling data via logging their start and stop timestamps. The sensor data collection functionality in ContextLogger3 is based Open Sensing Framework FUNF (funf.org) developed at MIT Media Lab [16]. For the pilot, we integrated the tools so that ContextLogger3 launched a CASS-Q questionnaire after a participant self-reported a change in his or her activity. This allowed context-contingent sampling for the questionnaires, albeit relying on self-reported contexts.

[1] CASS-Q client in Google Play: `https://play.google.com/store/apps/details?id=fi.metropolia.cass.main`

[2] ContextLogger3 source code: `https://github.com/apps8os/contextlogger3`

4.2 Research Design of Pilot Using the Framework

We limited the drain on the battery power by only taking collecting sensor data about the location using GPS coordinates and mobile network cell ids. The sampling rate was also conservative. This did also limit the amount of sensor data collected. We did not collect any data that could have compromised third party privacy, e.g., call logs or Bluetooth pairings. The participants were informed of the purpose of the study and what data was collected with particular care placed on informing them about sensor data collection. Each participant was asked to log the changes in their location and activity contexts throughout the day using ContextLogger3. After each change in their activity, the participants were prompted to answer a CASS-Q questionnaire 20 minutes later and subsequently in intervals of 60 minutes if the activity remained the same. Table 2 shows the contexts we collected data about, and the tools and methods used. CASS-Q data was uploaded to the management system after each questionnaire over either a WLAN or mobile network connection the smartphone was connected to at the time. Our participant group was not large enough to divide data collection burden amongst the group so we treated all of them equally in data collection with exception of retrospective interviews. We interviewed only a subset of the participants but this was more due to the ease the burden on researchers than the participants.

Table 2. Pilot data collection about contexts of mobile knowledge work

	Personal			**Environmental**		
	End user	**Social Environment**	**Activity/ Task**	**Conditions**	**Infrastructure**	**Location**
Profiled	Questionnaire for work flow and affect *(CASS-Q)*	Open question *(CASS-Q)*	Administrative / Research / Teaching & Supervising / Societal Activity / Other *(ContextLogger3)* Open question *(CASS-Q)*	Photograph *(CASS-Q)*		Semantic places: Home / Work / Customer / Public space / Transport *(ContextLogger3)* Open question *(CASS-Q)*
Sensed						GPS, cell id *(ContextLogger3)*
Derived		Indirectly via photograph *(CASS-Q)*			Indirectly via photograph *(CASS-Q)*	*Validation of changes in profiled location with sensed location data*
Timestamps (time of day and date) were stored for each sensor reading and user self-report via both ContextLogger3 and CASS-Q. This allowed us to analyze the duration of activities and time spent at the locations. Also, we used the timestamps to map flow and affect of work questionnaire answers from CASS-Q to the corresponding locations and activities reported via ContextLogger3.						

4.3 Phases of Data Collection in the Pilot

The participants downloaded and installed CASS-Q from Google Play while a version of ContextLogger3 with the specified location and activity contexts was downloaded from a separate web link. The participants then entered the unique identifier token they had received into CASS-Q and were then ready to begin data collection. We did not do pre- or post-study surveys. As ContextLogger3 does not include automatic inference of context from sensor data, we did not need to include a period of labeling training data for learning context inference algorithms either. After data collection, the activity and location context data from ContextLogger3 was used to create description of the working days of the participants. These were used in retrospective interviews with a subset of the participants. In the analysis phase we used the automatically collected sensor data to validate the self-reported changes in locations.

4.4 Experiences and Evaluation

The overriding conclusion from the pilot is that smartphone-based contextual research is a very promising and apt approach to study mobile knowledge work. We are still in the process of analyzing some of the data. Even such a short and small study like this resulted in rich and varied data that we could not have collected via traditional methods and tools. However, several challenges remain. Smartphones have different technical capabilities, run different versions of the operating system – or a different, incompatible with research application, and participants have data plans that differ in pricing and availability. We faced some problems with all of these issues in the pilot. We would assume the problems to be much bigger for a global study with larger sample sizes. While we collected the data successfully, its analysis still needs a lot of manual work. Raw sensor data needs to be cleaned from errors and transformed to formats used in common research tools.

5 Discussion and Conclusions

Our research revealed that mobile and multi-locational work can productively be studied by the smartphone-based research framework. In order to trace the increasingly turbulent, complex, and heterogeneous practices and contexts of mobile knowledge work, such new context and process sensitive methods are needed. We also show that the socio-digital technologies that increasingly mediate all aspects of modern work provide also instruments and methods for contextually tracing distributed personal and professional activities.

Yet, to transform the promise of smartphones as research instruments to reality, a great deal of research and development have to be carried out so as to have the following implemented in a single research toolset: full integration of automatic and self-report data collection; productive use of the smartphone sensor architecture while solving the associated energy consumption problems; implementing the algorithms for automatic context recognition being developed elsewhere; and d) effective analysis and visualization of large and complex bodies of time series data for purposes of scientific analysis and user feedback. Such a new generation research framework would allow more or less intelligently recognizing relevant contexts and use context-awareness for automatically activating queries [12]. To conclude, our long-standing strategic objective is to provide such a toolset for contextual and process-sensitive research in social and engineering sciences.

In social sciences, the method, so to speak, creates the phenomenon (=research object) investigated. The research instruments used determine what phenomena are visible and, thereby, subject to scientific scrutiny, and what remain in the background. From this perspective, the research framework could play an important role in making mobile knowledge work more readily accessible to scientific investigation than was previously possible. With further development, the smartphone-based instruments and methods to collect super-intensive data of participants and their group could have a big impact on social-scientific research in a larger scale (compare [17]). Using words of Stephen Intille, the ultimate aim must be to realize comprehensively ecological social science: *"With the technology available today, a comfortable device can be created that collects continuous stream of video data describing everything the subject sees, audio data of everything the subjects hears and says, accelerometer data of the subject's limb motion, data on physiological parameters such as heart rate, data on the subjects location on the community, as well as other miscellaneous data about how the subject is feeling, as reported by the subject via a mobile computing device user interface."* [18, p. 254], [12, p. 329].

Such ambitious goals are rarely achieved in isolation. Many of the available smartphone-based methods and instruments, including ours, rely on open source software. This enables large communities of investigators to jointly develop the tools and collect, share, store, and analyze data making the ultimate goal more attainable.

Smartphone-based research tool development and data collection both necessitate a careful consideration of the ethical issues involved. Participant privacy has to be protected both technically and with stringent ethical research guidelines.

This emerging research framework can be expanded beyond boundaries of mobile work. The methods and instruments are generic in nature; after creating a functional system for contextual assessment in the field of mobile work, the same tools and methods can be easily extended to neighboring areas, such as personal training, health interventions, and educational research.

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References

1. Verkasalo, H.: Contextual patterns in mobile service usage. Personal and Ubiquitous Computing 13(5), 331–342 (2009)
2. Lane, N.D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., Campbell, A.T.: A survey of mobile phone sensing. IEEE Communications Magazine 48(9), 140–150 (2010)

3. Khan, W., Xiang, Y., Aalsalem, M., Arshad, Q.: Mobile Phone Sensing Systems: A Survey. IEEE Communications Surveys & Tutorials 15(1), 402–427 (2012)
4. Soikkeli, T., Karikoski, J., Hämmäinen, H.: An end-user context framework for handset-based studies. In: The 19th ITS Biennial Conference, Bangkok, Thailand, pp. 18–21 (2012)
5. Bouwman, H., de Reuver, M., Heerschap, N., Verkasalo, H.: Opportunities and problems with automated data collection via smartphones. Mobile Media & Communication 1(1), 63–68 (2013)
6. Eagle, N.: Mobile phones as sensors for social research. In: Hesse-Biber, S.N. (ed.) Emergent Technologies in Social Research, pp. 492–521. Oxford University Press, New York (2011)
7. Intille, S.S.: Emerging Technology for Studying Daily Life. In: Mehl, M.R., Conner, T.S. (eds.) Handbook of Research Methods for Studying Daily Life, pp. 267–282. Guilford Press (2011)
8. Muukkonen, H., Inkinen, M., Kosonen, K., Hakkarainen, K., Karlgren, K., Lachmann, H., Vesikivi, P.: Research on knowledge practices with the Contextual Activity Sampling System. In: Proc. of the 9th Int. Conf. of Computer Supported Collaborative Learning, Rhodes, Greece, vol. 1, pp. 385–394. International Society of the Learning Sciences (2009)
9. Miller, G.: The smartphone psychology manifesto. Perspectives on Psychological Science 7(3), 221–237 (2012)
10. 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: 12th ACM Int.Conf. on Ubiquitous Computing, pp. 281–290 (2010)
11. Dey, A.K.: Understanding and using context. Personal and Ubiquitous Computing 5(1), 4–7 (2001)
12. Intille, S.S.: Technological innovations enabling automatic, context-sensitive ecological momentary assessment. In: Stone, A.A., Shiffman, S., Atienza, A.A., Nebeling, L. (eds.) The Science of Real-time Data Capture: Self-reports in Health Research, pp. 308–337. Oxford University Press, New York (2007)
13. Kahneman, D., Krueger, A.B., Schkade, D.A., Schwarz, N., Stone, A.A.: A survey method for characterizing daily life experience: The day reconstruction method. Science 306(5702), 1776–1780 (2004)
14. Muukkonen, H., Hakkarainen, K., Inkinen, M., Lonka, K., Salmela-Aro, K.: CASS-methods and tools for investigating higher education knowledge practices. In: Kanselaar, G., Jonker, V., Kirschner, P., Prins, F. (eds.) Int. Conf. for the Learning Sciences (ICLS 2008), vol. 2, pp. 107–115 (2008)
15. Mannonen, P., Karhu, K., Heiskala, M.: An approach for understanding personal mobile ecosystem in everyday context. In: Li, H., Järveläinen, J. (eds.) Effective, Agile, and Trusted eServices Co-Creation, 15th International Conference on Electronic Commerce (ICEC 2013). TUCS Lecture Notes, No 19, pp. 135–146 (August 2013)
16. Aharony, N., Pan, W., Ip, C., Khayal, I., Pentland, A.: Social fMRI: Investigating and shaping social mechanisms in the real world. Pervasive and Mobile Computing 7(6), 643–659 (2011)
17. Hey, T., Tansley, S., Tolle, K.: The Fourth Paradigm: Data-Intensive Scientific Discovery. Microsoft Research (2009)
18. Nusser, S.M., Intelle, S., Maitra, R.: Emerging technologies and next-generation intensive longitudinal data collection. In: Walls, T.A., Schafer, J.L. (eds.) Models for Intensive Longitudinal Data, pp. 254–278. Oxford University Press, New York (2006)