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*Review Article*

# Real-World Deployments of Participatory Sensing Applications: Current Trends and Future Directions

**Sameer Tilak**

*Qualcomm Institute, UCSD Division of the California Institute for Telecommunications and Information Technology (Calit2), 9500 Gilman Drive, La Jolla, CA 92093-0436, USA*

Correspondence should be addressed to Sameer Tilak; stilak@ucsd.edu

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With the advent of participatory sensing (sensors integrated with consumer electronics such as cell phones and carried by people), exciting new opportunities arise. Mobile sensors (e.g., those mounted on cars or carried by people) can provide spatial sampling diversity not possible with traditional static sensor networks. Recently, participatory sensing has attracted considerable attention of research community. In this paper, we survey existing participatory sensing deployments and discuss current trends and few possible future directions.

## 1. Introduction

As cell phones continue to become more resource-rich in terms of their processing power, memory, and display, they can support sophisticated applications ranging from browsing and messaging to navigation and gaming. The new generation cell phones have multiple embedded sensors (e.g., accelerometer, gyroscope, light, video, microphone, etc.) and can easily communicate with external sensors via any of the built-in interfaces including bluetooth, infrared, or WiFi. Currently there are more than 3 billion cell phone users in the world, and this number is increasing at an impressive rate. This makes cell phones an excellent platform for sensing the environment at unprecedented spatiotemporal granularity. For example, these cell phone users as they carry out their daily routine can use these sensors (either built-in or external or their combination) to gather data about their environment. For example, a sensor mounted on a vehicle can provide air quality observations from many locations throughout a day. The GPS information collected from people as they go about their daily lives gives us insight into public transportation systems at a level of granularity not possible before. In addition, personalized sensing provides sampling of phenomena as experienced by users, which allows us to track user experiences and support applications such as personalized medicine. In the last few years, participatory sensing has attracted a lot of attention of the sensor network research community [1–9]. There has been a number of participatory sensing deployments. However, to the best of our knowledge, there is no comprehensive survey of these deployments. In addition, details on common steps involved in building a participatory sensing application would be of great help to new researchers and focus groups. To that end, in the remainder of this section we give details on steps involved in building a participatory sensing application and describe different categories of these applications.

Goldman et al. [10] classified participatory sensing into following three categories. We now describe these categories along with motivating examples. In the later part, we also describe the steps involved in building these applications [10].

(i) Collective design and investigation: in this case, the participants are involved in all the phases of the project lifecycle. Participants collectively define the research objective(s) and finalize the sensors and their sampling frequencies, security policies, and data processing and management system. These participants have vested interest in the outcome of the study. Participants play an active role in the research rather than serving the role for a data collector. Imagine a community that believes that particulate matter released from a local factory is responsible for the

rise in cases of chronic diseases such as asthma and lung cancer in their neighborhood. They believe that although the data gathered by a couple of high-quality sensors deployed in the county of area 100 sq. miles is good enough to give a high-level picture, it does not reflect the quality of air they breathe in. These citizens are motivated to gather fine-grained data about air quality. This neighborhood has a wide variety of professionals—medical doctors, lawyers, engineers, and artists. Everyone is willing to contribute, and they actively participate and design the entire system. The system is then deployed, and high-frequency data is gathered for a period of 6 months. This data shows that the air contains significantly high amount of particulate matter in factory's neighborhood, and in particular it shows that it is directly related to the factory's production cycle. Understanding the environmental impact at the microlevel was not possible using just two existing sensors. These citizens can then use this data in their discussions with local policy makers and possible action such as improving manufacturing practices can be taken.

(ii) Public contribution: in this case, the participants are actively involved in the data collection phase but are not part of the group that defines the research objectives and necessary infrastructure (sensors and data management infrastructure). SETI@home [11] and Folding@home [12] are examples of very successful public volunteer computing projects where ordinary citizens although not involved in defining the research questions donated compute cycles of their personal computers to help the scientific discovery. One can easily extend this situation to participatory sensing environment. Consider a not-for-profit group that wants to document conditions of roads in a city since its members believe that potholes are primary causes of road accidents. The group has developed an open-source application that uses sensors embedded in cell phones (accelerometer, GPS, and gyroscope) to assess the road condition. Users can also give their input in the form of textual comments or pictures. All data will be anonymized and stored on a publicly accessible site. Anyone can just download and install this application on the phone. The participants can still have a vested interest in the project outcome, but unlike the first case, they are not involved in defining the research objectives or the software/hardware infrastructure, and participants merely act as data collectors.

(iii) Personal use and reflection: these participants are individuals focused on self-discovery and improvement. For example, imagine a busy businessman interested in gathering data about his eating, sleeping, and commute habits hoping to reveal hidden patterns in private and public behavior. He is also interested to know if the new medication has any impact on his eating habits and quantify the impact of his yoga sessions on his sleep quality. He wants to understand the relationship between his junk food consumption and stress level. He shares his walking routes with his buddies hoping to burn calories and eat more healthy food by learning new routes and food joints. He is using multiple sensors embedded in his cell phone and wears few sensors to gather this data. He shares this data with his friends and family. He is also sharing an anonymized version of this data on a public site hoping to learn from others. He is hoping to learn patterns that he is currently overlooking and then make positive changes in his lifestyle.

We now describe the steps involved in building a typical participatory sensing application.

(1) Recruitment and coordination: in this phase, groups get formed (either organically or in a top-down manner). Participants are provided necessary hardware (e.g., external sensors) and guidance for installation and configuration of the appropriate software. Participants are also informed about data access, security, and privacy policies, and typically their consent is taken before moving forward.

(2) Sensor data acquisition: participants now equipped with necessary software, hardware, and knowledge of the application start gathering data as they conduct their everyday life.

(3) Data transfer: the gathered data is moved over to a data center for long-term storage and processing. During configuration participants can select different data transfer policies. For example, participants with unlimited cellular data plan might allow transfer of data over both cellular and WiFi networks, while participants with limited cellular data plan might allow data transfer only over the WiFi network.

(4) Data management and storage: once the data is transferred to the data center it is stored (e.g., as files, or in a relational database management system, or even in a NoSQL database system). The data center can be simply a server hosted a university laboratory or a cluster hosted by a department on premises of a company or commercial cloud infrastructure such as Amazon EC2.

(5) Data analysis and visualization: the gathered data needs to be processed before it can provide any insight. This involves a myriad of data processing methods ranging from data cleaning to descriptive statistics to image processing and sophisticated machine learning algorithms. This step is typically application specific.

(6) Feedback/control: participants, scientists, or policy makers finally want actionable information. Action can be completely automated in the form of adaptive sampling (changing sampling rates) or actuation (turning sensors on/off) or they can be semiautomated (a trigger message asking user to change route) or manual (asking a plant to change its manufacturing process). Participants are hoping that the

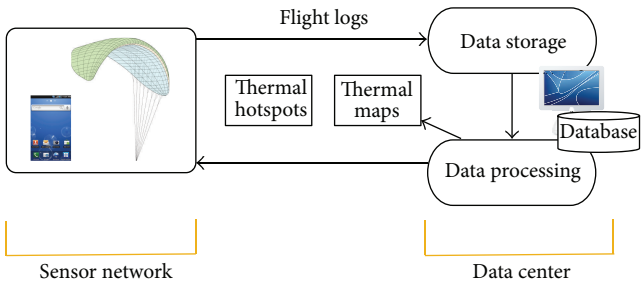


Figure 1: System architecture for a typical current generation personalized mobile sensing application.

feedback/control would bring about a positive change anywhere from an individual to societal scale.

## 2. System Architecture

Participatory sensing applications have two major components: (1) sensor network and (2) backend processing/data center. Figure 1 shows the system architecture for a participatory sensing application that exploits sensor data collected during cross-country flights by paraglider pilots to study thermal effects in the atmosphere [13]. The back end data center is a server where the data analysis and visualization services run for this particular application. Users then connect to the data center over the Internet and download/visualize the gathered data.

## 3. Survey

Participatory sensing presents an exciting opportunity and is likely to enable a new generation of applications capable of bringing about positive changes in lives of ordinary citizens at the societal scale over the next several years. It has a broad spectrum of applications including but not limited to environmental monitoring, intelligent transportation, personalized medicine, and to epidemiological investigations of disease vectors. Most of the current participatory sensing deployments fall in the following four areas (1) health and fitness, (2) environmental monitoring, (3) transportation and civil infrastructure monitoring, and (4) urban sensing. The goal of this paper is to present a survey of current participatory sensing deployments, and we do not survey existing system-level research (e.g., infrastructure services such as tasking, routing, etc.).

*3.1. Health and Fitness.* The potential for personalized and mobile sensing paradigm to transform healthcare and clinical intervention in the community is tremendous. It allows users to continuously and frequently track their health on the go and receive real-time user assistance when needed to alter their lifestyles. It enables health-care professionals to have access to comprehensive real-time patient data at the point of care. Not surprisingly, there has been a massive increase in the numbers of consumer smartphone apps (applications) downloaded over the past few years, with figures going up from 300 million apps downloaded in 2009 to five billion in 2010 [14], and there are already more than seven thousand documented cases of smartphone health apps [15].

Boulos et al. [16] give a brief overview of the state-of-the-art healthcare smartphone apps in the market. The paper describes apps targeting both laypersons/patients and healthcare professionals in various scenarios, for example, health, fitness, and lifestyle education and management apps; ambient-assisted living apps; continuing professional education tools; and apps for public health surveillance. Among the surveyed apps are those assisting in chronic disease management. In particular they developed eCAALYX, an Android smartphone app that receives input from a BAN (a patient-wearable smart garment with wireless health sensors) and the Global Positioning System (GPS) location sensor in the smartphone and communicates over the Internet with a remote server accessible by healthcare professionals who are in charge of the remote monitoring and management of the older patient with multiple chronic conditions.

Lane et al. [17] developed BeWell—a system that uses sensors embedded within a smartphone (gyroscope, accelerometer, microphone, camera, and digital compass) to enable a new class of personal wellbeing applications to monitor activities such as sleep, social interactions, and physical activity which in turn impact physical and mental health of an individual. Lu et al. [18] developed *StressSense*, a system that recognizes stress from human voice using smartphone. Their system can robustly recognize stress among multiple individuals in diverse acoustic environments.

Eisenman et al. [19] developed BikeNet, a mobile sensing system for mapping the cyclist experience. The system collects and stores data about the cycling performance metrics, including current speed, average speed, distance traveled, and calories burned over the long term. The gathered data is archived and analyzed for understanding long-term performance trends. For example, a cyclist can monitor his/her performance improvement or his/her exposure to health risks like automobile exhaust. The system also provides information to cyclists about the healthiness of a given route in terms of pollution levels, allergen levels, noise levels, and terrain roughness.

Biketastic is a platform that enriches this experimentation and route sharing process by letting bikers to document and share routes, ride statistics, sensed information to infer route roughness and noisiness, and media that documents ride experience [20]. The application running on a smartphone records high-frequency GPSdata (latitude, longitude, and speed) every 1 second. The microphone and the accelerometer embedded on the phone are sampled to infer route noise level and roughness. This will allow bikers to know the areas that have excessive noise levels, which could be indicators of large vehicles or heavy traffic. The onboard accelerometer is sampled to measure acceleration variance of the axis corresponding to the direction pointing towards earth, which gives an indication of divots and bumps. Authors evaluated the system based on feedback from expert bicyclists provided during a two-week trial period.

Ryder et al. [9] developed Ambulation—a mobility monitoring system that employs mobile phones to automatically detect a user's mobility mode using GPS data. The

gathered information is critical for patients suffering from mobility-affecting chronic diseases such as MS, Parkinson's, and Muscular Dystrophy. For energy efficiency, the system uses accelerometer as the means for detecting motion and triggering GPS.

AndWellness is a personal data collection system that uses mobile phones to collect and analyze data from onboard sensors and triggered user experience samples [21]. They have conducted a two week in-lab deployment of this system using the same campaign settings from a planned future deployment. They plan to deploy these systems for the following two applications: (1) to measure the behaviors and emotions of young breast cancer survivors and (2) to assess at risk HIV+ participants.

*3.2. Environmental Monitoring.* von Kaenel et al. [13] developed *Ikarus*, a participatory sensing application that exploits sensor data collected during cross-country flights by paraglider pilots to study thermal effects in the atmosphere. During their deployment, they collected data from 2,331 users with total raw data amounting to several Gb from 240,000 flights. Pilots record their GPS locations, barometric altitude, and timestamps during the flight. Flight tracks are uploaded to a central database of the community website and are stored in a format specified by the International Gliding Commission (IGC). These GPS tracks are then processed to generate probability maps of thermal columns. In addition, the coordinates of thermal hotspots can then be exported to the GPS devoice and be used during a flight. Their experience points three main challenges for the success of a participatory sensing application, namely, providing incentives for participants, ability to deal with faulty data, and concise data representation.

Paxton and Benford [22] conducted two participatory sensing deployments in the wild. The participants were groups of young people, who volunteered to collect and visualize environmental data in conjunction with contextual information, such as pictures, videos, GPS locations, and annotations. The focus of these deployments was to understand how participants interact with the sensors, how they carry out their tasks, their ability to collaborate with each other, and the implications the aforementioned factors had on the gathered data.

Mendez et al. [23] developed a system for air pollution monitoring and control. Their system includes sensors that measure $CO_2$, CO, temperate, relative humidity, and combustible gases in the atmosphere. Their backend system includes a server that hosts the gathered data and provides a platform for data analysis and visualization. They note that a participatory sensing application must provide a method to verify the validity of the data. For example, in the context of their application, users may fake the readings of the sensors (e.g., to avoid contamination fines). They point out that even though a lot of work has been done around the problem of multivariate statistical analysis and diagnosis of air pollution monitoring systems, most of this work does not consider the localization correlation of the measurements that a system with massive users would have. They also argue that the nonstationary characteristics of the air quality measurements imply sophisticated algorithms to infer and detect doubtful measurements, and further research is needed in this area.

Hasenfratz et al. [24] developed GasMobile, a small and portable measurement system using smartphones and off-the-shelf ozone sensor for air quality monitoring in urban environments. They used GasMobile to create good-quality air pollution maps with a high spatial resolution. They analyze the impact of mobility on data quality and also exploit the predeployed static sensor for calibrating the mobile sensors.

*3.3. Transportation and Civil Infrastructure Monitoring.* Mathur et al. [25] developed ParkNet, a mobile system comprising vehicles that collect parking space occupancy information while driving by. Each ParkNet vehicle is equipped with a GPS receiver and a passenger-side-facing ultrasonic range finder to determine parking spot occupancy. The data is sent to and aggregated at a central server, which builds a real-time map of parking availability and can provide this information to clients that query the system in search of parking. Using extensive GPS traces from over 500 San Francisco taxicabs, they show that if ParkNet was deployed in city taxicabs, the resulting mobile sensors would provide adequate coverage and be more cost-effective by an estimated factor of roughly 10–15 when compared to a sensor network with a dedicated sensor at every parking space.

Eriksson et al. [26] developed *Pothole Patrol*, a mobile sensor network for detecting and reporting the surface conditions of roads. The system was deployed on seven taxis running in the Boston area. Using a simple machine-learning approach, they show that the system was able to identify potholes and other severe road surface anomalies from accelerometer data. Thiagarajan et al. [27] developed *VTrack*, a system for travel time estimation using sensors onboard a smartphone. VTrack system uses the data gathered by CarTel system [4]. Mohan et al. [28] developed Nericell, a system for monitoring road and traffic conditions (to detect potholes, bumps, braking, and honking) in a city using accelerometer, microphone, GSM radio, and/or GPS sensors embedded in a smartphone. These existing deployments have generated considerable attention among domain experts and everyday citizens.

*3.4. Urban Sensing.* Miluzzo et al. [29] developed *VibN*, a mobile sensing application to determine *what is going on* around the user by exploiting multiple sensor feeds. Live sensor-feed allows the users to get an idea about live points of interest or *hotspots* of the city. Each hotspot is characterized by a demographics breakdown of inhabitants and a list of short audio clips. Additionally, the application automatically determines a user's personal points of interest based on historical data. This application is available for download in Apple App Store and the Android Market.

CenceMe combines the inferences of the presence of individuals using off-the-shelf, sensor-enabled mobile phones with sharing this information through social networking applications such as Facebook and MySpace [30]. In particular the system can automatically infer the user's presence (e.g., lunch at a Thai restaurant in downtown) and then shares this

presence through social networks. CenceMe was evaluated by 22 participants for over a three-week period.

Deng and Cox [31] developed *LiveCompare*, a system that leverages video cameras in smartphones for grocery bargain hunting. The system takes pictures of barcodes on grocery items and decodes the two-dimensional barcode to automatically identify grocery products and uses localization techniques to automatically pinpoint store locations. Their results show that an incentive scheme is inherently ingrained into the query/response protocol, and they suggest self-regulating mechanisms for preserving data integrity. They demonstrated that money-saving price comparisons can be conducted among brick and mortar grocery stores without the explicit cooperation of the stores.

Peebles et al. [32] developed Community-Guided Learning (CGL), a novel framework for learning models of human behavior from crowd-sourced sensor data. They argue that simply accepting freeform user-provided labels can be confusing and misleading. For example, users might use identical labels to different activities (e.g., labeling both dinner and lunch as "meal") or different labels to the same context ("driving" and "commute"). To that end, CGL provides a framework to build classifiers using inconsistently labeled sensor traces. They evaluated its performance using five participants and gathered a 33-hour audio dataset of high-level activities and their associated contexts. Participants provided freeform labels of their activities. Their results show that unlike existing techniques, CGL can cope with inconsistent labels which are norm in the real world.

Ahn et al. [33] developed MetroTrack—a system that uses mobile phones (with embedded sensors) for urban sensing and tracking. MetroTrack is responsive to the changing density of mobile phones and sensor network coverage. It tasks mobile sensors around a target event of interest and recovers lost targets by predicting the future location of the target and then tasking other mobile sensors in its close proximity. Their testbed comprised two N95 phones and nine N80 phones connected to nine Bluetooth GPS dongles. Their experimental results show that the system can effectively track a mobile noise source in an outdoor urban environment.

Table 1 summarizes the aforementioned deployments in terms of their hardware and software platform sensors used (both the embedded and the external sensors if any). Table 1 denotes the absence of the corresponding entity and NA denotes details not available in the literature. Table 1 shows that in 2007-2008 timeframe, Symbian OS was prominent in deployments, whereas in recent years Android has become more common. We conjecture that this is because Android is an open-source platform that is low-power and runs on a wide range of devices (phones, tablets, and embedded computers such as GumStix, Pandaboard). In addition, since Android applications are written in Java, developers find it easy to program. We also observe that most of the deployments use only the sensors embedded in the phone. In particular, only 5 out of 17 deployments use external sensors. This could be because the adding of external sensors increases overall energy consumption, cost, and form factor, thereby raising the deployment barrier. In addition, the cell phone is prepackaged with the software needed to acquire data from internal sensors. On the other hand, the development effort needed to integrate the external sensors could be nontrivial.

## 4. Future Directions

At present participatory sensing deployments are mainly small-scale research prototypes. However, their success will give rise to large-scale deployments involving hundreds of thousands to millions of users. These large-scale deployments will present unanticipated challenges in terms of scalability, reliability, management, and performance for both the sensor network component and the data center component. In particular, the current generation of participatory sensing applications has back-end infrastructure that is application specific and designed for and exposed only to a limited set of users [13, 23, 25, 27, 28, 31]. As an example, As shown in Figure 1, existing participatory sensing applications are primarily designed as standalone applications. Neither the hardware infrastructure nor the services are designed to scale out. The next generation of these applications will demand a scalable and elastic infrastructure that can scale out dynamically to hundreds of thousands to millions of users. For such large-scale participatory sensing applications, the computational, storage, and networking requirements of this back-end could be substantial. To that end, we argue to leverage cloud computing to provide a highly scalable, high-performance, pay-as-you-go, and grow-as-you-go environment that also reduces the infrastructure cost and development effort. Recent advances in cloud computing [34] make it an excellent choice for providing scalability and robustness while easing the development and IT overhead involved in the data center. In addition, basing the back-end on cloud computing will enable one to share the data more naturally and support application mashups that can draw on multiple data sources.

The success and increasing deployment of participatory sensor networks will drive towards a new generation that envisions a single user participating in multiple applications. Imagine a user participating in three applications: indoor air quality monitoring, road condition monitoring, and a smart health application that monitors impact of activities such as sleep, social interactions, and exercise on physical and mental health. Expecting users to manually enter the context (at home versus on the road) and start and stop applications is neither feasible nor scalable. The next generation applications demand an underlying infrastructure that will automatically infer the context and run applications appropriately. For example, ideally when the user is at home, only the indoor quality monitoring and smart health monitoring application should be run. When the user gets into his/her car, the indoor quality monitoring application needs to be stopped and the road monitoring application needs to be started to save the valuable resources such as memory and power.

Gamification stands for game thinking and game mechanics in nongame contexts in order to engage users and solve problems typically by giving reward points, achievement badges, or virtual currency [35]. Badgeville's Platform-as-a-Service (PaaS) allows web and mobile sites to measure and

Table 1: Summary of participatory sensing deployments.

| Application | Domain | Year | Hardware platform | Software platform | Built-in sensors | External sensors |
|---|---|---|---|---|---|---|
| BikeNet | 3.1 | 2007 | Nokia N80 | Symbian | Camera and microphone | Sensor interfaced with the Moteiv Tmote Invent |
| CenceMe | 3.4 | 2008 | Nokia N95 | Symbian | Accelerometer, microphone, camera, and GPS | X |
| Pothole patrol | 3.3 | 2008 | Soekris 4801 | Linux | Accelerometer, GPS | X |
| Nericell | 3.3 | 2008 | HP iPAQ hw6965, HTC Typhoon | Windows Mobile | Microphone, camera, GPS, and accelerometer | X |
| VTrack | 3.3 | 2009 | Soekris 4801 | Linux | GPS | X |
| LiveCompare | 3.4 | 2009 | Nokia N95 | Symbian | Camera, GPS | X |
| Ambulation | 3.1 | 2009 | Android phone, Nokia N95 | Android, Symbian | GPS | X |
| MetroTrack | 3.4 | 2010 | Nokia N80 and N95 | Symbian | Microphone, camera, GPS | X |
| CGL | 3.4 | 2010 | iPhone | iOS | Audio | X |
| ParkNet | 3.3 | 2010 | Embedded computer | NA | X | Ultrasonic range finder, GPS |
| AndWellness | 3.1 | 2010 | Google G1 | Android | GPS and the accelerometer | X |
| Ikarus | 3.2 | 2011 | Flight recording device | X | GPS, barometric | X |
| Biketastic | 3.1 | 2011 | Google G1 | Android | GPS, microphone, and accelerometer | X |
| BeWell | 3.1 | 2011 | Nexus One | Android | Gyroscope, accelerometer, microphone, camera, and digital compass | X |
| eCAALYX | 3.1 | 2011 | Nexus One | Android | GPS | Smart garment (no details on sensors) |
| GasMobile | 3.2 | 2012 | HTC Hero | Android | X | Ozone |
| StressSense | 3.1 | 2012 | Samsung Nexus S, Samsung Galaxy Nexus | Android | Microphone | GSR sensor |

influence user behavior using techniques including gamification and game mechanics, social mechanics, and reputation mechanics [36]. Recently launched Fitocracy is a social network that uses gamification to help users improve their fitness [37]. The current generation participatory sensing deployments are small, and face-to-face meetings and personal connections can keep the participants motivated for the project duration. However, for the next generation deployments involving hundreds of thousands participants to keep them engaged throughout the deployment duration, face-to-face meetings or personal phone calls will not scale. We argue that the next generation participatory sensing deployments for their sustainability need to make gamification technique an integral part of their design and implementation.

## 5. Conclusion

Participatory sensing paradigm by actively involving ordinary citizens to gather high-resolution spatiotemporal data about the natural and the built environment has a potential to bring about positive changes at the societal scale. In this paper, we surveyed existing participatory sensing deployments in four domains, namely, healthcare, transportation and civil infrastructure monitoring, environmental monitoring, and urban sensing. Although these deployments are still primarily limited to small-scale research prototypes, they show that their results are quite promising. We observed in the last couple of years that deployments are migrating toward Android platform. We also discussed few possible future directions that would allow us to truly harness the potential of participatory sensing paradigm.

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