University “Politehnica” of Bucharest

Automatic Control and Computers Faculty,
Computer Science and Engineering Department

MASTER THESIS

Intertial sensors in crowd sensing applications

Scientific Advisers:
Cristian Chilipirea
Ciprian Dobre

Author:
Vlad Ioan Nistorica

Bucharest, 2016

Abstract

Having access to up-to-date and accurate information about the environment can be important for both environmental scientist, city planners, park administrators and also regular users. One way of capturing this type of data is through inertial sensors. An example of application for inertial data can be surface movements like earthquakes or vibrations caused by diferrent factors, while other can include gesture recognition, user behavior in specific spaces or analysing the terrain that the user is going through.

Powerfull applications can be built from gathering inertial data from a large number of devices with inertial sensors. This can be achived through crowd sensing. Other alternatives for acquiring such data by hand or by deploying sensor networks would be expensive and time consuming. Also, people without proper scientific training want to take part in the data acquisition process and assist with the needs of their respective communities.

Crowdsensing is a technology-driven area where ICT platforms are being developed which permit anyone to participate in processes that help expand our understanding and improve our surroundings. Crowdsensing refers to the process in which crowds (large number of people) measure specific features and share the resulting data or send it to a central location in which it can be used by the people that need it. Since the increase in popularity of smartphones, which are now ubiquitous, crowdsensing is more popular than ever.

A lot of people can now participate to crowdsensing but we still don't know how many are needed for a crowdsensing campaign to be successful. In order to answer this question, we built a simulator that mimics the characteristics of a crowdsensing campaign. We showcase three different scenarios in which we estimate the required number of participants and offer a discussion on the plausibility of having that many participants by taking into account factors such as accessibility to the area of interest (the area from which the measurements are needed).

Also, using crowd sensing, a use case is proposed and analysed in more detail. We propose a way to gather information about location of stairs and elevators, using gesture recognition, that could help disabeled persons calculate paths to diferent destinations.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Crowd Sensing

There is a need for up to date, detailed data on different metrics that characterize the environments we live in. A few examples are: air quality, noise pollution, traffic density and even WiFi access. This data is significant to environmental scientists, city managers and even citizens which can make better, informed, decisions. Data is the first step in enabling smart cities.

Standard solutions for gathering environmental data on a large geographical scale are expensive and difficult to implement. Even community driven projects such as the Air Quality Egg[1] come at a high price and have moderate usage (in the order of thousands for the entire planet). A recent alternative that is growing in popularity is crowdsensing (Section ??). Crowdsensing [15] proposes the distribution of the data gathering task to a large number of people. Any person carrying a device capable of measuring a certain characteristic of the environment and transmitting this data to a central database can participate in a crowdsensing campaign.

Smartphones represent the most convenient tool for a crowd sensing campaign. First of all, smartphones are now ubiquitous, meaning the cost of deploying a crowdsensing campaign is lowered because most people already own the hardware needed for such a campaign. According to [13], in United States the penetration of smartphones has reach a percentage of 72% and even in less developed countries the percentage of smartphone penetration is rising fast. They have a large variety of sensors, such as accelerometers, microphones and video cameras and can easily be extended with more through the use of Bluetooth. They have more and more powerful processors, which permit complex data processing, as well as clear methods of developing and deploying new applications that can run on a very large number of devices. Lastly all smartphones have WiFi and LTE modules which permit the transmission of the sensed data.

For crowdsensing, to be effective, it still has to deal with a number of pitfalls. Crowdsensing campaigns require a significant number of participants in order to permit the extraction of valid conclusions (a.k.a., a critical mass of people is needed in order to validate the measurements). These campaigns are either volunteer-based or offer special incentives, such as monetary compensation [14]. In either case, it is not clear how many participants are needed in order to have a successful crowdsensing campaign, where enough data is gathered to permit the organizers to draw valid conclusions. To our knowledge, there are no studies that offer a methodology for determining a threshold for an optimal number of participants of a crowdsensing campaign. The optimal number is the minimal number of participants for which enough data is gathered. The number of participants needs to be minimal in order to minimize resource usage and incentives costs.

[1] http://airqualityegg.com/

In this paper we propose a methodology for computing the optimal number of participants for a crowdsensing campaign depending on the campaign characteristics. Having this number is vital for the organizers of any campaign that uses crowdsensing techniques. First of all, it offers an idea of the possible success (as in, how representative is the measurement data to describe a particular environment) of the campaign. Secondly, a relation between the number of participants and the effectiveness of the measurement sensing campaign, can in fact help the organizers plan the use of incentives to either motivate participation, or keep the costs under control.

Determining an optimal number of participants in real life is difficult. Starting a crowd sensing application is currently based on the willingness of people to participate. It is unlikely and extremely time consuming to repeat the same crowdsensing campaign with varying number of participants.

No trivial solutions for determining the optimal number of participants are available. An obvious one would be to divide the size of the area of interest, by the size of the sensing area of a single sensor. The solution is appropriate for static sensors. However, it does not take into account overlaps between multiple sensors or movements of the sensors, as they are carry around by people, during a time period. When we take movement into account a single sensor can cover a far larger area then it is expected from its specification.

Our approach for determining the optimal number of participants is to simulate crowdsensing campaigns that take into account crowd movement (Section **??**). We choose an interest area, Herastrau park in Bucharest, and simulate crowdsensing campaigns for air quality, WiFi access as well as people density as crowd sensing applications (Section **??**).

We take a further look into the problem of the number of participants by offering a discussion on the number of possible candidates for a crowd sensing campaign. Possible candidates represent people for which taking part in the campaign is reasonable. To offer a clear example, it is wrong to assume that a crowd sensing campaign could have more participants than the number of citizens of the respective city the campaign takes place in (Section **??**).

1.2 Accelerometers

Inertial sensors are one of the most used components, because of the multitude of applications that can be build from inertial information, low costs and easy integration in different types of hardware, like mobile phones, robots, drones and many more. The role of an inertial sensor is to identfy phisical movement, which can be liniar displacement or rotation, and transform it to a readable set of analogical or digital data.

An inertial sensor commonly uses one or more accelerometers and gyroscopes and ranges from low cost, MEMS inertial sensors, measuring only a few square mm, that offer less precision, up to more precise and expensive sensors, like ring laser gyroscopes which can measure 50 cm in diameter. Most common types of sensors are MEMS (Microelectromechani- cal) inertaial sensors, which can be found in most smartphones, drones, head mount displayes, IoT applications and others. For example a Nexus 5 smartphone uses InvenSense MPU- 6515 six-axis, which is a MEMS MotionTracking device and includes capacitive gyros and accelerometers. The same IMU is used in [7] for detecting unsafe driving.

Magnetic sensors can also be used as a referance, in order to minimize the gyroscope drift.

In an inertial system, the information from different sensors are fused toghether to have the result that is expected. In general, for fusing these types of information a Kalman filter is used, which is able to combine data from several different environments that have outputs with noise.

The role of this filter is to use the combined data to reduce the weak point of sensors, so that combining the best parts of different types of sensors can result in better precision.

1.3 Accelerometer in crowd sensing applications

To give a more specific implementation, we take into consideration the use of inertial sensors in the context of crowd sensing, because inertial sesors, in particular accelerometers and gyroscops, are present in most of the smartphones and have a large number of applicable use cases.

Our use case takes into consideration the use of smartphones to recognize when a user is using stairs or an elevator. Using data agregated from a large number of smartphones, a map of stairs and elevators can be built, with minimum effort and costs. The beneficiaries for this map could be people with disabilities, that could route their path to a destination according to this information.

For this use case, firstly, an Android application will be built for creating testing and training datasets. The training and testing data will be pre-segmented. If present, magnetic and gravitational sensor will be used to reduce drift and normalize the capture data.

In the second step, a gesture recognition pipeline will be proposed, which will contain algorithms for pre-processing, so that the noise for the captured data is reduced, for gesture recognition, which will identify 4 actions: stairs up, stairs down, elevator up and elevator down and post-processing algorithms.

The last step, will be to test how fast the pipeling learns the actions and compare different algoritms results.

Chapter 2

Related Work

2.1 Crowd Sensing

Crowdsensing is still a young scientific area but it has already gathered a lot of interest and support, as we show below. There are a great number of studies that show the diversity of scenarios in which crowdsensing can be applied.

As stated in [6] and [5], crowdsensing can provide micro and macroscopic analysis of cities, communities and persons. It can be applied in social networking, health, energy, monitoring human behavior and many others.

In terms of environmental analysis, the authors of [3] show that by using crowdsensing in urban areas one can collect traffic data or generate noise maps. A similar solution, regarding noise pollution in urban areas is presented in [17]. Air quality analysis represents another interesting use for crowdsensing. Authors in [21] claim that crowdsensing is the optimal solution for capturing data for large areas, although it is only feasible for CO_2 emissions, because of the complexity and cost of other sensors. [8] adds road surface monitoring and street parking availability. The former article also presents two categories of sensing: participatory, in which users have to get involved and be active in the measurement and data acquisition process, and opportunistic, where the user has a more limited role in the sensing. In fact, the second sensing approach tends to also be more visible in the literature and existing platforms for crowdsensing, because the user is relieved of much of the burdens associated with taking decisions where and how to collect measurement data. Our work focuses on the second approach, opportunistic sensing.

Without the use of crowdsensing the cost of implementing a similarly capable sensor system would be significantly higher. In [9] the authors show that to cover an area of approximatively $1km^2$, 100 sensors and 1096 relays need to be used. This method cannot scale for larger area of studies, so crowd sensing is a better alternative.

As described in [14], crowd sensing generally implies a requester, a campaign starter, which requires users willing to capture sensor data that is used directly or at a later time for various experiments. The authors acknowledge that in terms of user engagement, it is sometimes difficult to convince users to participate in a crowdsensing analysis. Incentives are proposed as a solution to this problem. They take the form of payments or gamification. Incentives are also used in [18]. The authors use micro-payments and gamification to attract enough users so that they can cover the area of a university campus. The scope was to measure WiFi signal strength across the entire campus. However, the authors make no analysis on what is the optimal number of participants to a crowd sensing campaign or how to manage incentives to reach that value.

The use of payments for crowd sensing participation without a previous analysis of possible number of participants could lead to high costs and little control over the results.

Access to a space of interest. It is not enough to determine the optimal number of participants for a crowd sensing campaign. One also needs to take into account the plausibility of achieving this number. Probably one of the factors that is most relevant is the accessibility of individuals to the area of interest. In the literature there are different approaches to determine the number of people that have access to an area, such as a park, some of which are presented below.

The authors of [11] present the travel cost approach. They show two methods of measuring the accessibility to a park using geographical information. In the first, the service area of the park is considered a circle, with the radius equal to the maximum desired distance between the center of the park and locations of visitors. The disadvantage of this method is that park visitors are assumed to be able to reach the park by using a straight line, which is not usually the case. The second method is based on the shortest path algorithm using the boundary of the park area and the streets and paths that the visitors can walk on. Their work takes into account both neighborhood parks (2 - 4 ha) and mini neighborhood and community parks (0.4 - 2 ha). The total distance accepted is less than 0.8 km of walking.

The main problem with this approach is that visitors do not always use the closest park and tend to travel more for a park that has a bigger area or more facilities compared to the ones offered by a closer park. An alternative would be consider the distance cost to all parks in the studied area, or a predefined set. Using this method, a set of 3 parks and limited number of people it has been demonstrated [4] that visitors prefer parks that offer more attractiveness even if they are not in close proximity.

The authors of [19] use the container approach to determine the equity and accessibility to public playground. An extension of this method is the kernel algorithm presented in [10]. The Kernel density estimation method can give an accessibility rating for every point in the studied area. The idea behind this method is to rate every acre that is studied as belonging to a park or not and using kernel density algorithm, the area is converted to a statistical surface. The problem with this method is that depending on the kernel bandwidth taken into consideration, there could be areas that have no accessibility, which is incorrect.

The attractiveness of a park can be modeled by using as little as only the size of a park. The assumption is that larger parks have more facilities and respectively are more attractive. In [20] the authors propose the population-weighted distance, which should be a more precise method of determining the accessibility to a park. This is the method we chose for our analysis and discussion.

2.2 Accelerometers

Chapter 3

Experimental analysis

3.1 Simulating a crowd sensing campaign

In order to simulate a crowd sensing campaign, we require a set of characteristics for the campaign. A campaign can be characterized by the area of interest, the zone from which the data needs to be gathered, the range at which a sensor can measure data and the time the campaign is expected to take place.

A WiFi sensor can detect hotspots at ranges of about 100m, according to the WiFi 802.11 standards[1]. In contrast, an air quality sensor can take measurements of the air that directly touches it. For the later one we assume the measurements are relevant for a distance of 3m.

The area of interest can have highly irregular shapes. Consider a park, not only is the outer perimeter of the park often irregular, but a park may contain features that are not accessible to pedestrians such as small lakes. In order to have an accurate representation we extract the zone of interest from Open Street Maps[2]. The simulator takes the given area and the number of participants and generates their movement. We use random walk in order to simulate the movement of the individuals over a period of time.

In order to verify the correctness of our simulator we built a small visualization tool. A NodeJS server offers the simulation data to a JavaScript tool that makes use of the Google Maps[3] library in order to display the locations of individuals inside the area of interest. An example of the visualization can be observed in Figures 3.1. The area of park Herastrau, as described in Open Street Maps, is represented with red and the small white discs represent pedestrians.

Because the shape of the interest space can be bounded by an irregular polygon, in order to calculate its area, we use grid sampling. We take an outer rectangle that encapsulates the entire area and split it in a grid of 1000 by 1000 cells. We then count the total number of cells that are inside the polygon. Finally, we multiply the total number of cells inside the area of interest with the area of a cell.

To determine if a cell is inside the polygon describing the interest space we use a ray casting algorithm [16]. In ray casting a set of parallel lines are drawn over the rectangle. We start in the upper left corner and use vertical lines. The intersections between these lines and the polygon are calculated. For each cell, if the number of intersections is even, it means the cell is inside the polygon and thus inside the area of interest, otherwise it means the cell is outside.

[1] http://standards.ieee.org/about/get/802/802.11.html
[2] https://www.openstreetmap.org
[3] https://www.google.ro/maps

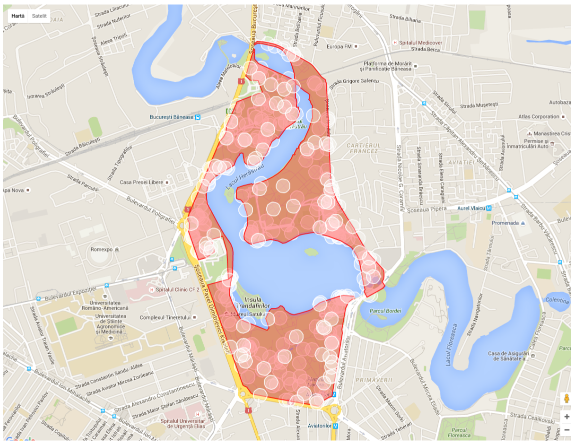

Figure 3.1: Simulation, 100 persons, sensing area radius of 50m

In order to simulate pedestrians, we randomly choose their starting location as points inside the area of the park. We generate random locations inside the outer rectangle and keep only those that are inside the polygon. In order to determine if the location is inside the space of interest we used the same ray casting method.

To have a more realistic simulation we added movement. Crowdsensing campaigns use pedestrians or even vehicles. In our experiments we focused on spaces such as parks through which only pedestrians can move. We set the same speed of 5km/h for all simulated individuals. The speed was chosen according to [1]. The movement was simulated using the Random Walk [12] algorithm. In random walk, pedestrians move in a randomly chosen direction until they reach the edge of the interest space. In our case we consider collisions with any element of the polygons. Because we focus on parks, there can be multiple polygons. As we stated earlier, parks can have features that are not accessible by pedestrians, such as small lakes. Each of these are bounded by a polygon. When we detect a collision for a pedestrian another direction is chosen randomly and the pedestrian continues its movement in the new direction with the same speed.

In order to simulate the data gathering process we use discs of a set radius centered on each of the pedestrians. In reality the shape of the detection area for a sensor is highly irregular. Take WiFi, where the shape of the area in which frames can be correctly received varies with irregularities of the antenna, features of the environment and even weather. Because the shape varies from sensor to sensor and there is no model that describes the irregularities found in nature a disc can be used as an acceptable approximation.

In order to calculate the area of the surface of the interest space covered by at least one of the sensors carried by the pedestrians we use the same grid sampling method. In this case, a cell represents an area that we consider to be covered by a sensor if there exist at least one sensor whose disc covers at least half of the cell. In order to determine if a cell is inside a disc we calculated the Euclidean distance [2] from the center of the cell to the position of any pedestrian. If, for any pedestrian, this distance is smaller than the sensing radius we consider the cell to be covered by the sensors. This is described in equation 3.1, where x_c and y_c represent the location of the center of the cell and x_p and y_p represent the location of a pedestrian.

$$\forall i; \sqrt{(x_c - x_{p_i})^2 + (y_c - y_{p_i})^2} < sensingRadius \tag{3.1}$$

The final goal of the simulation is, given a sensing radius, an area of interest and a time period, to determine the percentage of the area of interest that is covered by sensors. After we count the number of cells covered by the sensors and the number of cells inside the area of interest we use equation 3.2 in order to determine the percentage of the area covered by sensors. For a cell to be considered covered it needs to have been inside the disc of a sensor at any point in time during the simulation.

$$coveredPercentage = \frac{count_{coveredCells}}{count_{spaceOfInterestCells}} * 100 \tag{3.2}$$

3.2 Accelerometers

Appendix A

Project Build System Makefiles

A.1 Makefile.test

```
# Makefile containing targets specific to testing

TEST_CASE_SPEC_FILE=full_test_spec.odt
API_COVERAGE_FILE=api_coverage.csv
REQUIREMENTS_COVERAGE_FILE=requirements_coverage.csv
TEST_REPORT_FILE=test_report.odt


# Test Case Specification targets

.PHONY: full_spec
full_spec: $(TEST_CASE_SPEC_FILE)
	@echo
	@echo "Generated␣full␣Test␣Case␣Specification␣into␣\"$^\""
	@echo "Please␣remove␣manually␣the␣generated␣file."

.PHONY: $(TEST_CASE_SPEC_FILE)
$(TEST_CASE_SPEC_FILE):
	$(TEST_ROOT)/common/tools/generate_all_spec.py --format=odt -o $@ $(TEST_ROOT)/functional-tests $(TEST_ROOT)/performance-tests $(TEST_ROOT)/robustness-tests
#

# ...
```

Listing A.1: Testing Targets Makefile (Makefile.test)

Bibliography

[1] Nick Carey. Establishing pedestrian walking speeds. *Portland State University*, 2005.

[2] Michel Marie Deza and Elena Deza. *Encyclopedia of distances*. Springer, 2009.

[3] Bin Guo, Zhiwen Yu, Xingshe Zhou, and Daqing Zhang. From participatory sensing to mobile crowd sensing. In *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2014 IEEE International Conference on*, pages 593–598. IEEE, 2014.

[4] Pawinee Iamtrakul, Kardi Teknomo, and Kazunori Hokao. Public park valuation using travel cost method. In *Proceedings of the Eastern Asia Society for Transportation Studies*, volume 5, pages 1249–1264. Citeseer, 2005.

[5] Wazir Zada Khan, Yang Xiang, Mohammed Y Aalsalem, and Quratulain Arshad. Mobile phone sensing systems: A survey. *Communications Surveys & Tutorials, IEEE*, 15(1):402–427, 2013.

[6] Nicholas D Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, and Andrew T Campbell. A survey of mobile phone sensing. *Communications Magazine, IEEE*, 48(9):140–150, 2010.

[7] et al. Liu, Luyang. Toward detection of unsafe driving with wearables. *Proceedings of the 2015 workshop on Wearable Systems and Applications. ACM.*, 2015.

[8] Huadong Ma, Dong Zhao, and Peiyan Yuan. Opportunities in mobile crowd sensing. *Communications Magazine, IEEE*, 52(8):29–35, 2014.

[9] Xufei Mao, Xin Miao, Yuan He, Xiang-Yang Li, and Yunhao Liu. Citysee: Urban co 2 monitoring with sensors. In *INFOCOM, 2012 Proceedings IEEE*, pages 1611–1619. IEEE, 2012.

[10] Andrew R Maroko, Juliana A Maantay, Nancy L Sohler, Kristen L Grady, and Peter S Arno. The complexities of measuring access to parks and physical activity sites in new york city: a quantitative and qualitative approach. *International Journal of Health Geographics*, 8(1):1, 2009.

[11] Sarah Nicholls. Measuring the accessibility and equity of public parks: a case study using gis. *Managing leisure*, 6(4):201–219, 2001.

[12] Karl Pearson. The problem of the random walk. *Nature*, 72:342, 1905.

[13] Jacob Poushter. Smartphone ownership and internet usage continues to climb in emerging economies, 2016.

[14] Moo-Ryong Ra, Bin Liu, Tom F La Porta, and Ramesh Govindan. Medusa: A programming framework for crowd-sensing applications. In *Proceedings of the 10th international conference on Mobile systems, applications, and services*, pages 337–350. ACM, 2012.

[15] Oriana Riva and Cristian Borcea. The urbanet revolution: Sensor power to the people! *Pervasive Computing, IEEE*, 6(2):41–49, 2007.

[16] Scott D Roth. Ray casting for modeling solids. *Computer graphics and image processing*, 18(2):109–144, 1982.

[17] Matthias Stevens and Ellie D'Hondt. Crowdsourcing of pollution data using smartphones. In *Workshop on Ubiquitous Crowdsourcing*, 2010.

[18] Manoop Talasila, Reza Curtmola, and Cristian Borcea. Crowdsensing in the wild with aliens and micro-payments. *under submission in IEEE Pervasive Computing Magazine*, 2014.

[19] Emily Talen and Luc Anselin. Assessing spatial equity: an evaluation of measures of accessibility to public playgrounds. *Environment and Planning a*, 30(4):595–613, 1998.

[20] Xingyou Zhang, Hua Lu, and James B Holt. Modeling spatial accessibility to parks: a national study. *International Journal of Health Geographics*, 10(1):1, 2011.

[21] Yu Zheng, Furui Liu, and Hsun-Ping Hsieh. U-air: When urban air quality inference meets big data. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1436–1444. ACM, 2013.