Crowdsensing Smart City Parking Monitoring

Félix Jesús Villanueva, David Villa, Maria José Santofimia, Jesús Barba, Juan Carlos López
Department of Information Technologies and Systems
School of Computer Science
Ciudad Real, Spain
{*felix.villanueva, david.villa, mariajose.santofimia, jesus.barba, juancarlos.lopez*}*@uclm.es*

***Abstract*—Free parking search is one of the citizen's daily tasks which influences the most in the overall city performance. Pollution, traffic and productivity are deteriorated by cars looking for a place to park. In this paper, we propose the use of one of the features present in today's mobile phones, the magnetometer, to get a real-time map about free spaces in the street. We will demonstrate the viability of our work and preliminary results showing how the magnetometer "feels" the surrounding environment.**

***Keywords*-Smart City, Crowdsensing, smart phone sensors, magnetometer, parking problem.**

I. Introduction

Over the past ten years the evolution of mobile phones held by citizens have originated new solutions and services. Crowdsensing is a technique oriented to recollect data from citizens so as to provide them with advanced services by means of smart data analysis which leads to the extraction of useful information. Activity detection and geofencing [1], urban environment sound and road conditions [2] and tourist services [3] are examples of such city services which can be improved by means of crowdsensing collaboration.

Looking for free parking space is probably one of the most frustrating tasks in the daily routine of citizens [4]. Also, pollution, noise, traffic jams could be improved by reducing the amount of time that any citizen spends looking for a free parking space. It has been estimated that, in our cities, up to 30% of the traffic is due to vehicles looking for a place to park [5]. Our research initial hypothesis is, would it be possible to use the magnetic sensor embedded in our mobile phone to detect adyacents cars?. Let us imagine that we park our car in the parking of a shopping center, would our mobile phones be able to detect if adyacents parking space are free or occupied? If so, we could automatically elaborate a hot map displaying free parking spaces.

These initial questions raised when we were evaluating the sensibility of the current magnetometers embedded in today's smart phones. The use of this kind of sensors is being applied to other research fields in works such as the one carried out by [6] who can even indoor positioning a user thanks to a magnetic field fingerprint collected in a database with high precision/accuracy. Our motivation is to study the viability of the use of magnetometers for a collaborative elaboration of a free-space parking map.

In this on-going work, our main contribution is an empirical study to demonstrate the feasibility of using mobile phone magnetic sensors for free park detection. Finally, it is worth mentioning that all the test scenarios described in this paper were recorded at the parking of the School of Computer Science (Ciudad Real, Spain), a closed and controlled environment. As we will see later, the promising results motivate us to extend the scenarios to streets, shopping centers parking, etc.

The remainder of this article is organized as follows. Next section describes briefly the state of art regarding free parking detection. Section III thoroughly describes the test-bed design and structure of the experiment. Sections IV, V and VI shows preliminary results about sensibility of the magnetometer in three different test-beds. Finally, last section describes some conclusions and future work.

II. Related work

The problem of free parking search has been addressed by scientific community in different ways. Parking availability prediction [7],smart traffic management [8], architectures for parking management [9], etc are examples of different approaches to mitigate the problems related with have a great number of citizens driving just for searching free parking spaces (noise, pollution, efficiency, etc.).

One of the key problems to address this issue is to effectively detect available parking slots. There are numerous technologies proposed for this purpose, in [10] a 3D Photonic-Mixer-Device camera is used to detect the free space of a parking slot, infrared sensors are used in [11] to design a real-time monitoring system for parking space management services. Other technologies like scanning laser radar-based system [12], also have been used for monitoring free parking spaces. In [13] an on-site deployment of sensors to monitor and to signalize the state of availability of each single parking space is developed.

All these methods are costly and/or require of an infrastructure support. Our method is based in a magnetometer sensor which is embedded in most of the current mobile-phones. Our idea is to develop an App which enable the collaboration between citizens to share their sensor information in exchange for getting the information of available parking spaces whenever they need it.

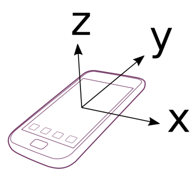

Figure 1. Magnetometer

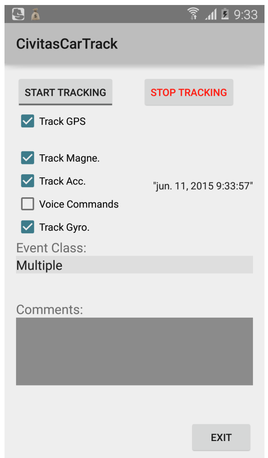

Figure 2. Android App to track test files

III. Test-bed design

As we will see later, we designed three test-bed in order to check the viability of our proposal. For all the test-beds we used a Samsung Galaxy S4 mobile phone inside of the test-car (Hyunday ix35) attached to the windscreen by a support (Figure 3) in such way that the mobile phone always has a vertical position. This is important in order to analyze the axis involved in each test-bed (Figure 1). The magnetometer, which readings are in microtesla (µT) units, is a sensor used for measuring magnetic forces or the disturbance in the Earth's magnetic field. This magnetic field is not parallel to surface, it has inclination and it is not aligned with axis of rotation so it is important the sensor orientation when the signal is processed.

In figure 2 the Android app used for getting track files is shown. The App generates two files per each track session, the first file is a configuration file where comments about the content of the monitoring tracking session, mobile phone orientation matrix and the #eventclass being monitored is stored. These files have the extension .metadata, an example of this type of file looks:

```
#ssn
Car stopped, Engine stopped, There is no cars both sides
    of the test car.

Rotation Matrix:
0.58487785, −0.15769249, 0.795645, 0.0, 0.8094017,
    0.04962474, −0.58515495,
```

Figure 3. The cartrack app running

```
0.0, 0.05279085, 0.98624057, 0.15666096, 0.0, 0.0, 0.0,
    0.0, 1.0,
```

Another file with the same name but with .csv extension is generated with all information about sensors. According to the desired sensors (mainly magnetometer in this work), the SCVfile stores the raw readings of the sensors together with a timestamp and a header indicating the meaning of each column:

```
time , Magx, Magy, Magz
1418233669643, 8.719, −87.195, −254.537
1418233669654, 9.196, −86.844, −250.335
1418233669676, 9.507, −85.888, −247.869
1418233669694, 9.507, −84.89, −245.276
.....
....
```

The name of the file is the date of test-bed together with a tag that the user can add to identify the content of the test-bed.

IV. Scenario I: Magnetometer sensibility basic scenario

The first scenario is to test if the magnetometer is sensible to the presence of a car close to the test-car. Additionally we want also check the influence of the engine running in the magnetometers readings. We define 6 different classes of events showed in the figure 4. We have 3 free parking spaces (figure 4 [A]) where we are going to place the test-car (represented by grey car in the figures).

The first event is showed in the figure 4 [B], there is no car at both side of the test-car, in order to test the influence of the engine in the magnetic field, we make 2 classes of this emplacement configuration, the first is with the engine stopped and the second with the engine running. The events are labeled with three letters representing the state of the engine (r→ running or s→ stopped), the state of the car (r→ running or s→ stopped) which is always stopped in the

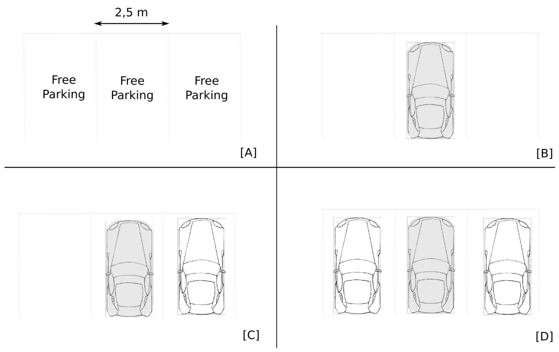

Figure 4. Parking monitoring scenario

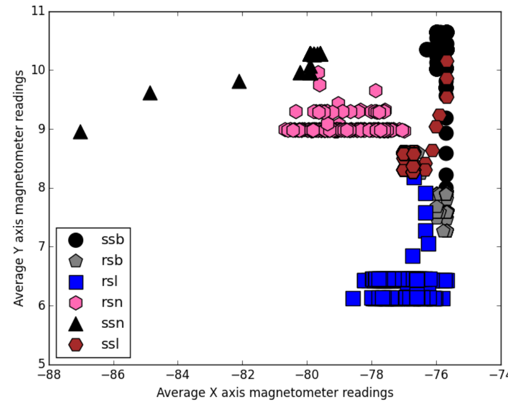

Figure 5. Points of magnetometer readings

first scenario and if there is no car at both sides of the test-car (identified with letter n), if there is a car to the left of test-car (identified with letter l)[1] and finally, if there are cars both sides of the test-car are identified with letter b. So with this definition, an event labelled with rsb letters represents that the engine is running, the car is parked and there are cars to both sides of the test-car (Figure 4[D]).

So summarizing we have the following possibilities:

- ssb: engine stopped, car stopped, there are cars both sides of test-car (figure 4[D])
- rsb: engine running, car stopped, there are cars both sides of test-car (figure 4[D])
- rsl: engine running, car stopped, there is a car at the left side of test-car (figure 4[C])
- rsn: engine running, car stopped, there is no car close to the test-car (figure 4[B])
- ssn: engine stopped, car stopped, there is no car close to the test-car (figure 4[B])
- ssl: engine stopped, car stopped, there is a car at the left side of test-car (figure 4[C])

In order to analyze the magnetometer readings we represented in a graphic all the *points* of each class. Each *point* represents a configurable number of raw readings, for this test-bed we choose 3 readings per each point so we calculated the average and the standard deviation of each axis and then, we added the tag of the class to which belongs that point. The influence of a car close to the test-car is significant and can be showed clearly when we place all the points in a graphic representing the influence of each scenario in the axis X and axis Y of the magnetometer. This graphic is the figure 5 where we can see, for each class defined, how the readings are grouped so a clustering technique could help us to identify the situation of the test-car when, for example, is parked in a parking.

We can also appreciate that the engine state (on/off) has a significant influence in magnetometer readings. The feasibility of apply a supervised learning method is supported by the clustering groups that we can intuitively see in figure5.

We use Support vector machines (SVMs), a set of supervised learning methods used for classification, and specifically, we build a model using an implementation of *Support Vector Classification* for multiclass support which is handled according to one-vs-one scheme [14]. Specifically we use the algorithm implementation done by *sklearn* library [15] (version 0.16).

There are 1307 points tagged with one of the six classes defined. The algorithm SVC takes 980 points to build a model and then, validates the model with the rest of 327 points. By doing this, the algorithm has a hit rate of 93% in the worst case. Figure 6 and Figure 7 show the confusion and normalized confusion matrix for the model generated. The configuration parameters are:

```
class sklearn.svm.SVC(C=1.0, kernel='rbf', degree
    =3, gamma=0.0, coef0=0.0, shrinking=True,
    probability=False, tol=0.001, cache_size=200,
    class_weight=None, verbose=False, max_iter=-1,
     random_state=None)
```

Using this model, any car could send its readings to a server which could estimate the situation around the car which sent the readings identifying if there are a car parked right/left, both sides or none of them. In last term and together with GPS information, the server could do a heat map of free parking spaces.

V. Scenario II: Magnetometer sensibility on movement

The second scenario is devoted to see the sensibility on movement of the test-car to a free-space (figure 8), in this case we have a row of cars with a free parking space (figure 9) in the middle of the row. The test-car passes at 6km/h following the row in a similar way that a car pass by, for example, a shopping center car parking. The intention

[1] the equivalent scenario with a car parked on the right side of the test-car has been omitted due its equivalence to the left side.

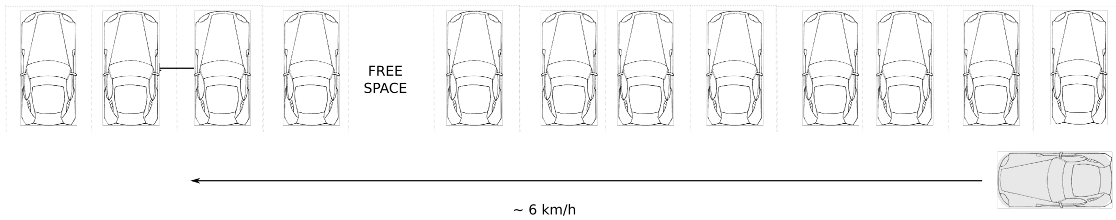

Figure 8. Movement Parking monitoring scenario

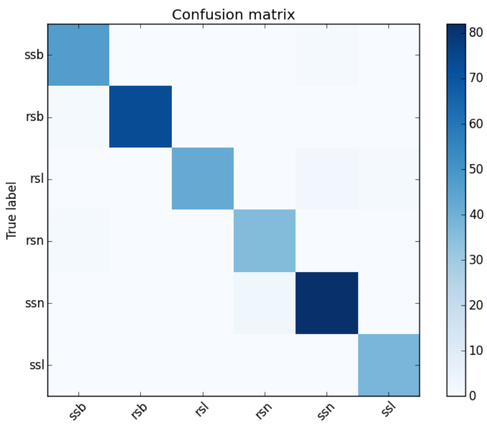

Figure 6. Confusion matrix

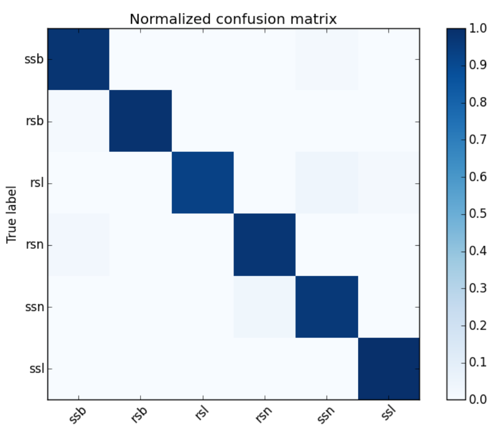

Figure 7. Normalized confusion matrix

of this scenario is to check if there is a response in the magnetometer sensibility.

We start this test-bed with the test-car stopped at the end of the line of cars, at 10th second we start to move at around 6km/h. 6km/h is equivalent to 1.6 m/s and each parking space has 2.5 m width. In the test-bed, the free parking space is placed in the 8th position so we have around 20m that the test-car takes 12.5 seconds to pass near the free parking

Figure 9. Test-bed scenario

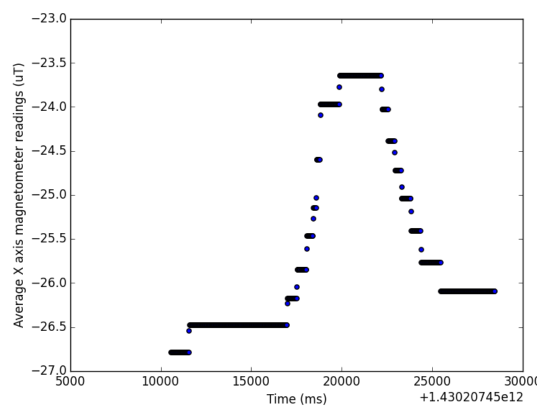

Figure 10. axis X of readings of magnetometer in movement

space. We should see variations around 22.5 second.

Again, the most representative influence is in X axis, as we can see in the figure 10 there is a strong variation around the second 22 as we expected so we should be able to identify when there is a free parking space close to the test-car. Also in the Y axis we can see a significantly influence (figure 11).

VI. Scenario III: Distance Magnetometer Sensibility

The third scenario is to see the sensibility of the magnetometer to the distance to a parked car, just to check if we

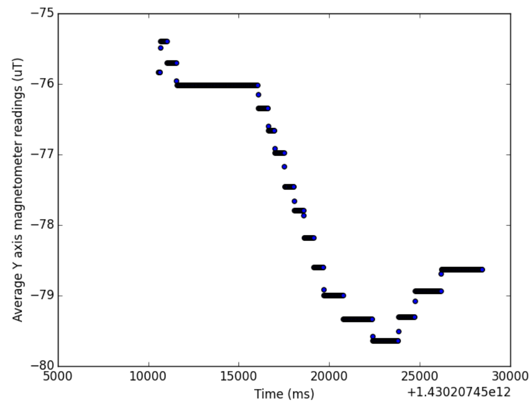

Figure 11. axis Y of readings of magnetometer in movement

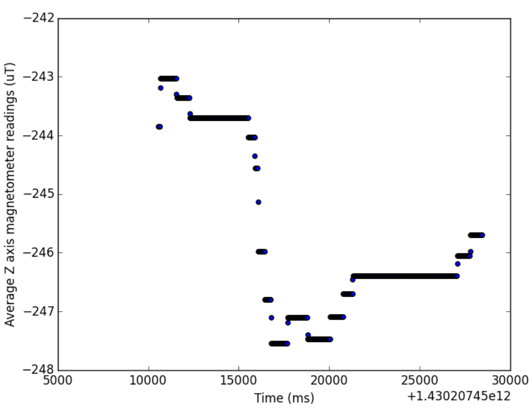

Figure 12. axis Z of readings of magnetometer in movement

Figure 13. Distance sensibility scenario

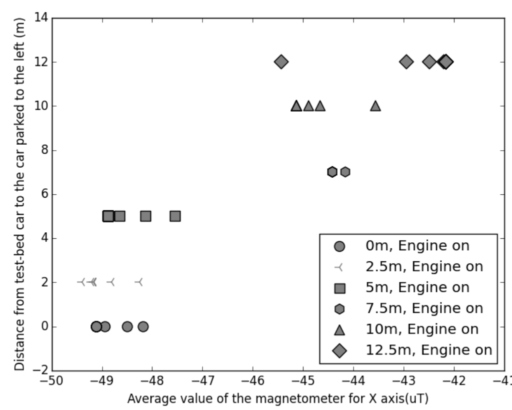

Figure 14. Readings of X axis magnetometer according to the distance (Engine On)

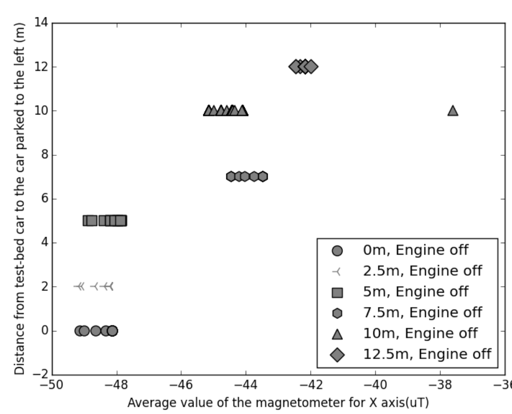

Figure 15. Readings of X axis magnetometer according to the distance (Engine Off)

can differentiate the distance between the test-car and the parked car. Again we only check with a car parked in a side (to the left in this case). The reader can see this configuration in figure 13 where the test-car is moved far-away of the car parked to a distance of 0 meters (figure 13[A]), 2.5 meters (figure 13[B]), 5 meters (figure 13[C]), etc.

As we can see in figure 14 and figure 15, in spite that we can appreciate a correlation between the distance and the X axis readings, it will be difficult to appreciate or to estimate the number of free spaces available between two cars. The Y axis help us to detect if there is a car close to us, but it is useless in major distances. Again there is a slightly difference between the test with the engine on (figure 14) and with the engine off (figure 15).

VII. Conclusions

In this paper we show an on going work about the feasibility to use magnetometer sensors embedded in the user mobile phones as scanner of available parking spaces. As we have shown, there are promising results in detecting cars parked close to the test-car (the car with the mobile phone) and also on detecting available parking spaces on movement. There are more difficult if we want know the distance between two cars by using the magnetometer. For reproducibility reasons, the dataset and scripts used for analyzing the data can be found in a public repository.[2]

This paper shows the feasibility of applications by automatically detects available parking spaces in the city. A crowdsensing app could elaborates a hot map about available parking spaces shared with citizens who share the information of their mobile phones.

Our current work is devoted to design and to implement the first prototype of the crowdsensing App based on the first scenario results. Our idea is to elaborate a real-time map of the available parking spaces.

Of course we are aware that we need to record a more wide scenarios in order to analyze multitude variables (different test-car magnetic fingerprinting, different mobile phone sensors, different velocity, car placement, etc.,). Currently, we are asking for permissions in order to make full test-bed in open spaces (public streets and a big supermarket parking) but we wanted to ensure to have preliminary results that partially support our research hypothesis.

Acknowledgment

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