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Estimation of Spatial Density Using Bluetooth Sampling

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ABSTRACT

Mobile computing is one of upcoming technologies with different models and methods. In wireless we have a lot of efficient technologies that are improved a lot day by day. In mobile communication they had implement different sensors for roaming device to watch map and play games multi touch etc. In this project we are trying to find spatial density of people with the help of Bluetooth radiation, which may be of big help in finding various applications in various fields. For example, in the field of urban analysis, estimating spatial density is important to create evacuation plan, to plan a new location for department store, business people can use it to find the flow of people crowd and calculate and start their business accordingly. The spatial density of population is measure of people present in different location within an area of interest. This process takes place with the help of probes; probes may be of any form, example mobile, person, cameras etc. If the total population of the area of the interest is known, then the non monitored density can be found by minus the number of spatial density in monitored area. However, if the population size is unknown then estimating spatial density becomes more challenging as people present in non monitored area is unknown, and here is where pattern-likelihood maximization and sequence probability estimation is implemented.

Keywords: *Population size, Density estimation, opportunistic sampling, Bluetooth sampling*

1. INTRODUCTION

Knowing the density of a crowd can be relevant for a number of applications. Examples range from crowd control and emergency services through urban planning to consumer applications recommending where to go out (based where many other people also have gone to).While in some applications dedicated infrastructure such as access control gates or CCTV cameras may be used, in others it would be desirable to be able to estimate crowd density without preinstalled infrastructure. One possibility is to recruit enough
users to be able to estimate the density from the number of devices which report being in the relevant area. The obvious disadvantage of this method is that a significant number of users must be recruited, which is not always possible. In this paper we present an alternative method that requires only few users moving through the environment with their mobiles

scanning for discoverable Bluetooth devices. The paper builds on previous work directed to using Bluetooth scans to analyze social context and extends it with more advanced features, leveraging collaboration between numerous devices, and the use of relative features that do not directly depend on the absolute number of devices in the environment.

The method is evaluated on an extensive data set from a three-day-long experiment. Estimating population size and population density finds applications in various fields. For example, ecologists and biologists are interested in estimating the population sizes of certain animal species. In the field of urban analysis, estimating population density is important, e.g., to create evacuation paths, to plan new locations for department. Social networking applications such as activity-hotspot detection, make use of population density to pinpoint night-life hotspots to users of the application. A particularly interesting feature is that when they are in visible mode, phones broadcast their MAC address, which makes them uniquely identifiable. This possibility enables us to use mobile phones as sensing devices and to evaluate different features related to the mobility patterns of the population. A practical challenge in our approach knows the percentage of visible Bluetooth devices in the population. On average, close to 8:2 percent of people carry Bluetooth devices with activated detection functionality, which is large enough to make possible density estimations from Bluetooth measurements.

2. LITERATUR SURVEY

The work most similar to ours is by Nicolai et al. [5] where the discovery time of Bluetooth devices as well as the relation between number of people and number of discoverable Bluetooth devices was investigated. As opposed to our approach the work relied on static Bluetooth sensing locations and only the absolute number of discovered Bluetooth devices was used. Along the same lines Morrison et al. [4] investigated crowd density estimation in stadium based sporting events. However they did not attempt rigorous automatic classification and focused on a visualization tool for Bluetooth logs. Another use case of Bluetooth scanning is described in [3] by Kostakos. They recorded passenger journeys in public transportation by analyzing Bluetooth fingerprints. In [6] O'Neill et al. presented initial findings in Bluetooth presence and Bluetooth naming practices. Finally, slightly further away from our work, Eagle et al. showed [2] how to recognize social patterns in daily user activity, infer relationships and identify socially significant locations from using Bluetooth scans. BLIP Systems [1] exploited a stationary Bluetooth based people tracking system. Based on multiple Bluetooth zones scenarios like queue length at airports or travel times by car are indicated.

3. COLLABORATED ESTIMATION

Collaborated crowd density estimation relies on multiple users walking through the same space. The analysis combines the scan results of their devices computing the following features:

Feature 1.collaborated: Average number of devices

Feature 2.collaborated: Variance of the number of devices

Feature 3.collaborated: Variance of all signal strengths

Figure 1. People per metre in average

The first feature (Average number of Bluetooth devices) is computed by collecting Feature 1.individual of each participating sensing device and averaging the values. As opposed to a sum, this feature is independent of the number of collaborating devices.

Figur.2. people per metre in average

The second feature (Variance in the number of devices) is defined by the variance of the individual ’Feature1. Individual’ values across all devices (variance (i)! = var(number x(i)) where i is the time frame and device x 2 S given S as the set of sensing devices).

Figure 3. People per metre in average

The third feature (Variance of all signal strengths) is defined by the variance of the signal strengths aggregated from all participating sensing devices during a given scan interval. Potential multiple occurrences of the same Bluetooth device found by different sensing devices are not removed from the feature computation. Figure 3 presents the extracted features from the raw data.

4. OBTAINED MEASUREMENTS

For the entrance phones, we consider only the Bluetooth traces that were collected during the opening hours of the festival. In total, 3,326 different Bluetooth devices were discovered at the entrances. The estimated number of attendees (obtained on the basis of the number of tickets sold and the tickets punched at the entrance gates), which was provided to us by the organizers of the festival, is 40,536. From these two numbers, we get 8:2 percent as the approximate percentage of attendees who have visible Bluetooth devices. This ratio depends on many factors such as the characteristics of the population (e.g. age). Other estimated ratios reported in the literature are as follows: 4:7 to 7 percent in a campus bar [13], 8 to 12:5 percent in an airport [17], 11 percent in a cultural and theater festival [15], and 13 percent in a sports event [16]. As the entrance phones can discover all the visible Bluetooth devices upon their arrival and departure, we can compute the empirical arrival/departure time distribution of the visible Bluetooth devices. The empirical marginal distributions of the visible Bluetooth devices arrival times, departure times, and the duration of stay on the festival grounds.

: Position of the (static) entrance phones

Figure 4.Ground truth image in crowd

The foundation of our Bluetooth based spatial Density using bluetooth sampling technique is based on the general observation that many people have the Bluetooth transceivers of their mobile phone in the discoverable mode as default setting. The other data sets were collected for different purposes, such as inertial navigation and activity recognition. However all data sets include regular Bluetooth scans collected over periods of days by several volunteers walking through the area of the specific event during times of different crowd density. It can be seen that the median of the number of devices discovered per scan is between 8 and 13 with thousands of distinct devices having been recognized over the course of each experiment. This scenario shows that only less than 10% of the scans returned no discoverable devices and up to 50 devices were seen when in dense crowd.

We observed that most discoverable Bluetooth devices are smart phones and cell phones mostly manufactured by Samsung, Nokia and Sony Ericsson. While in a dense crowd with a few hundred people we may get a representative sample, in less crowded areas we are likely to see very strong variations between samples. Assuming the probability of any single user having a discoverable Bluetooth device to be 10% the probability that no device is seen when 20 people are within range is 0.9 20 = 0.12. Thus we may sometimes be in a group of people who do not even have activated mobile phones while at other times we may be surrounded by a group where everyone has an active Bluetooth device for their details updating on common cloud storage system.

5. WORKING OF AGENTS

Agents have to register with their particular IMEI address and sample the visible Bluetooth devices in a population. Store the MAC address of the visible devices in the database in order to avoid the conflict of Bluetooth names.

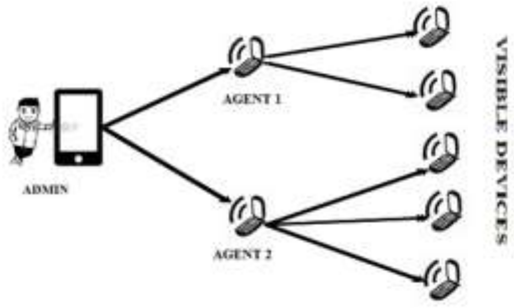

Figure 5.Module description

Admin can view the agent details. Spatial density comparison and overall monitoring are done by admin via graphical representation. Bluetooth present in agent mobile devices are used to search other Bluetooth signals every 80sec and a count is taken. Repetition of devices is not possible as MAC address of the device is taken and processed. Agent location is received using GPS which can be viewed in order to see specific area count. Comparison are different agents is how in graphical view for better understanding of the result. All this process is maintained in Admin mobile and also several mobile devices can also act as agents.

6. FUTURE THREATS

As if now the project is done with the help of Bluetooth , which is a low range of signal in this point of time, whereas in the future this project can be carried out with the help of Wi-Fi signals which has high range and also has wide area of signal strength.

7. CONCLUSION

We have shown how Bluetooth scan data from just a few users equipped with standard mobile phones can be used to estimate crowd density. The core of the method is the comparison and fusion of data from different devices which leads to over 30% improvement in accuracy over a simple single device approach. The just over 80% accuracy on four classes must be seen in the context of noisy ground truth resulting from arbitrary class definition, extrapolation between photos taken every 500m, and inaccuracies in the counting process. In addition, confusions occur nearly exclusively between neighboring classes (see figure 7). Note that the experimental data did not include the ”nearly empty space” class which can be trivially recognized from the near absence of Bluetooth devices and could be easily integrated into the system. In summary, we believe that the method presented in this paper is potentially useful for many applications. To further improve it future work will focus on better understanding and modeling the relative features. We will also collect data from other events and countries to verify the hypothesis that the relative features are robust against culture related differences in the percentage of people carrying discoverable Bluetooth devices.

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