Potential and Implications of Bluetooth Proximity-Based Tracking in Moving Object Research

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1. Introduction

The increasing use of localization technologies in mobile devices such as cell phones offer the ability to record large volumes of tracking data. Analysis of these data may offer valuable insights for domains such as mobility, security and tourism. As a consequence, geographic knowledge discovery has evolved as a new and rapidly growing research area at the intersection of various research domains such as geographical information science and computer science (Miller and Han 2001). Since GPS currently constitutes the most common localization technology and offers detailed tracking data, most of the empirical research concerning 'moving objects' has focused on analyzing GPS tracks. Yet, other tracking technologies are also available, and are sometimes more suitable for meeting certain research goals. Bluetooth, for example, also offers the potential to track individuals by tracking their mobile devices, and is currently better tailored for anonymously studying the movements of large crowds at mass events. To date, however, the process of Bluetooth tracking, as well as the interpretation of the resulting data, have received only scant attention in GIScience literature. Therefore, further investigation is necessary both with respect to the tracking process itself and the analysis potential of the resulting data.

2. Why Bluetooth?

In order to study the movement dynamics of crowds, tracking data are needed from individuals within this crowd. The larger the sample of tracked individuals is, the more reliable the results will be. Two important factors influence the relative size of this sample set: (i) penetration of the technology in mobile devices and (ii) the degree of active involvement of the tracked individual. Whenever active participation of the individuals is required, some of these individuals will either not know how to participate or choose not too (e.g. due to privacy concerns).

Although it can be expected that integration of GPS in mobile devices will rise in the future, the current penetration rate in mobile devices remains low (Ratti et al. 2006). In addition, it always requires active participation of individuals. For analysis, the GPS track needs to be moved to a central server through a network connection, which involves some kind of authorization from the individual carrying the mobile device. Bluetooth tracking, however, does not necessarily involve the tracked individual in any way (Hay and Harle 2009). In addition, the current penetration of Bluetooth in mobile devices is quite high in comparison with the GPS technology. Despite the ability to turn off the Bluetooth functionality on a device, recent experiments have shown that it is possible to track at least 10% of all individuals attending a mass-event (Van Londersele et al. 2009).

Another key advantage of Bluetooth tracking is its applicability in indoor as well as outdoor environments, whereas conventional GPS positioning is impossible in indoor environments (Zeimpekis et al. 2003).

3. How does Bluetooth tracking work?

Bluetooth was originally developed as a short-range communication technology between mobile devices, and is currently the *de facto* technology for easily sharing information (contacts, images, video) between devices in each other's vicinity. In order to communicate between devices, both devices need to know which other devices are within their communication range. This is done by broadcasting a device inquiry. Such a scan typically lasts 10.24 seconds (Peterson et al. 2006), and returns a list of devices identified by their MAC-address (i.e. a unique identifier linked to each Bluetooth device).

Generally speaking, there are two potential methods of using this technology as a tracking technology: proximity-based and multilateration of the signal strength. Since Bluetooth signals only propagate over a limited distance, the detection of a mobile device at a sensor with a known location implies that the device was within the communication range of the sensor. This method of extracting rough location information is generally known as proximity-based positioning. The theoretical communication range of the sensors used in our experiments (class 2) is around 10m. The actual range, however, which depends on various factors such as reflections and hardware quality, is usually somewhat higher (~30m). During the device inquiry, the received signal strength intensity (RSSI) at which a mobile device is detected can also be recorded. Because this intensity usually decreases with increasing distance, it is theoretically possible to get an estimate of the distance from the sensor by correlating the RSSI values with distance in prior experiments (Hossain and Soh 2007). By estimating this distance from multiple sensors at different locations, one could theoretically multilaterate in order to get an estimation of the actual location of the mobile device (Awad et al. 2007). Multilateration potentially offers more detailed motion information than proximity measurements, but remains problematic to date because of the imperfect correlation between RSSI and distance (Hossain and Soh 2007). Therefore, we will focus on proximity-based tracking in the remainder of this paper.

4. Bluetooth proximity-based tracking data

Bluetooth scanners installed across the study area continuously scan for other devices. When a mobile device is detected, an 'in' registration with its MAC-address and a timestamp gets registered. Then, when this device is not detected anymore for at least 10.24 seconds (the duration of a scan cycle), an 'out' registration with another timestamp gets registered. In this way, it is possible to trace individual mobile devices because it is known where (location of the scanner) and when ('in' until 'out') a certain mobile device (MAC-address) was. The following is an extract of a log file of a Bluetooth scanner showing three mobile devices that were detected:

```
1246525539,0021080577xx,5898756,in
1246525544,0021080577xx,5898756,out
1246525429,0019B74FABxx,5243404,in
1246525575,0019B74FABxx,5243404,out
1246525558,001E3A5C31xx,5898756,in
1246525590,001E3A5C31xx,5898756,out
```

The general format of a log line is: timestamp (unix format), MAC-address, device class code, in/out. The device class code contains information about what kind of mobile device (cell phone, smart phone, handsfree kit, etc.) is associated with the MAC-address.

5. Characteristics of Bluetooth proximity data

The special nature of proximity tracking data can be illustrated by Figure 1:

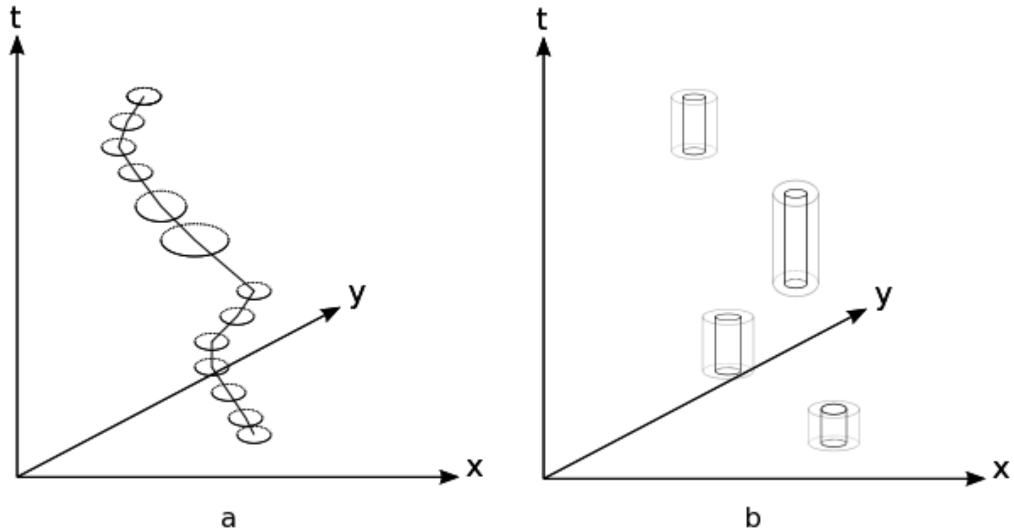

Figure 1. GPS data (a) and Bluetooth proximity tracking data (b) visualized in a conventional space-time aquarium.

Where GPS tracking data (a) are practically continuous in both space and time, Bluetooth proximity data (b) are inherently discrete. Locations that are not covered by a scanner do not provide any movement information. Additionally, the location calculations in the GPS tracks are linked to a single point in time, whereas the proximity-based data consist out of time intervals during which the mobile device was detected somewhere.

Both types of tracking data are inherently characterized by a limited accuracy which diminishes the reliability of the measurements. Whereas the only uncertainty in GPS tracking data lies in the position estimation at each timestamp (depicted by the variable ellipses in Figure 1a), the uncertainty in Bluetooth proximity tracking data is more complex and embedded in both space and time. Due to the potential delay between a device entering the communication range and its detection, the 'in' and 'out' time registrations are never exact. The spatial uncertainty is actually twofold. First, in unconstrained space, a mobile device can only be assumed to be within a circular region around the sensor. Second, the actual communication range is not crisp but fuzzy where the likelihood of getting detected decreases as one moves away from the Bluetooth sensor (depicted by the double boundary of the cylinders in Figure 1b). Because the propagation of Bluetooth is highly susceptible to influencing factors such as reflections by obstacles there is also a chance that a device that is within range does not get detected.

6. Analysis potential

Hence, Bluetooth proximity tracking data are much coarser than GPS tracking data and cannot be converted into detailed geospatial lifelines (Hornsby and Egenhofer 2002). As a consequence, some finer-grained motion attributes such as instantaneous speed, acceleration or motion azimuth cannot be extracted. This limits the application potential of existing analysis methods using such motion attributes to extract higher-level patterns and knowledge (Laube et al. 2005). Future queries such as in Future Temporal Logic (Wolfson et al. 1998) also become challenging. A more promising method to extract valuable information is sequence analysis (Shoval and Isaacson 2007). Additionally, more general yet insightful indicators providing static information from one sensor can be readily extracted from the tracking data. An example of this is shown in Figure 2 which depicts the varying crowdedness around a Bluetooth sensor placed at the entrance of a rock festival attracting around 100.000 visitors per day. A typical pattern is visible where there is a gradual influx of visitors during the afternoon, followed by a much sharper efflux at night. Over the course of four days, a total number of around 23.000 mobile devices were detected by 36 sensors across the festival area (Van Londersele et al. 2009).

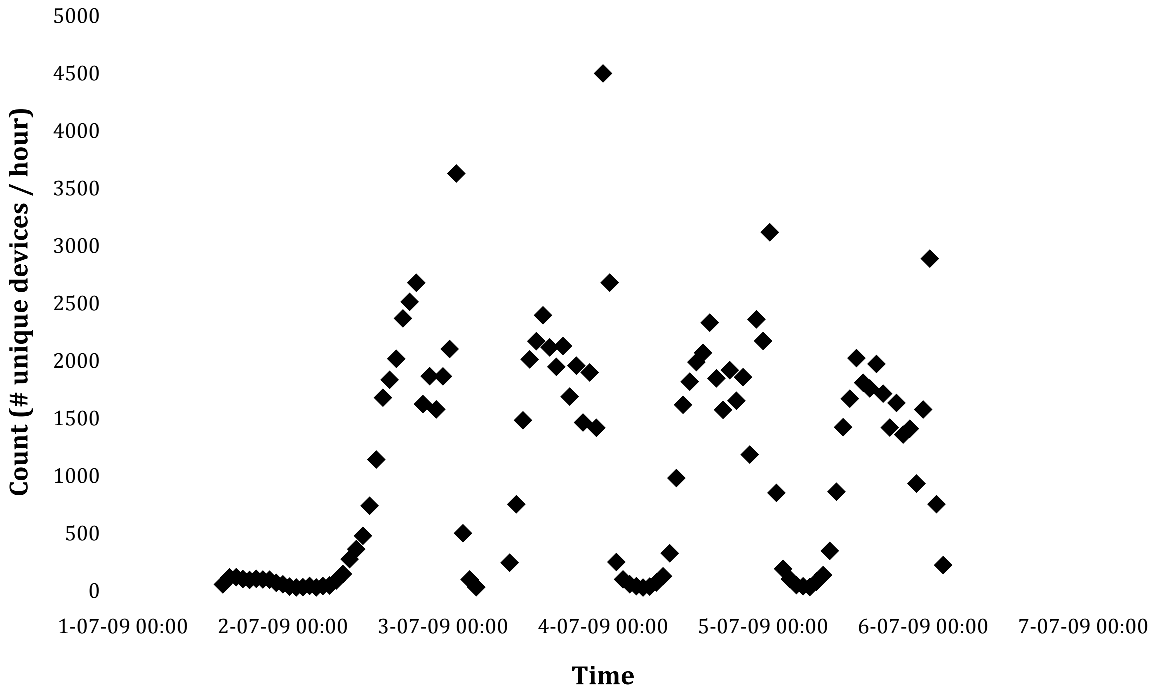

Figure 2. Hourly counts of unique mobile devices detected within the communication range of a Bluetooth sensor.

A GIS for Moving Objects (GISMO) is currently developed in java for analyzing the data. A screenshot is shown in Figure 3.

7. Conclusion and open research questions

Bluetooth proximity-based tracking offers an alternative way of generating massive amounts of tracking data, but its true analysis potential remains hard to predict. Do completely new methods need to be developed, or can some of the current methods be adapted to support these data? Ultimately, how can we extract interesting patterns from these trajectories?

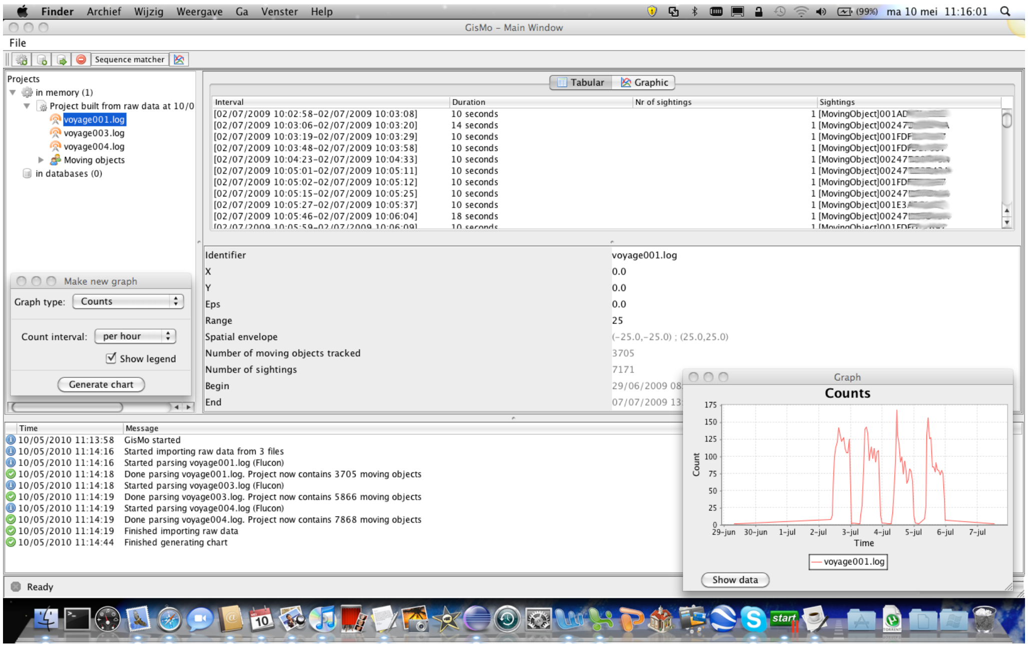

Figure 3. Screenshot of GISMO.

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