A Preliminary Study on Trajectory Sensing and Data Reduction in Mobile Terminal

Guangwen Liu †, Masayuki Iwai † and Kaoru Sezaki ‡

† Institute of Industrial Science, University of Tokyo
4-6-1 Komaba, Meguro-ku, Tokyo, 153-8505, Japan
‡ Center for Spatial Information Science, University of Tokyo
Email: † liugw198209@mcl.iis.u-tokyo.ac.jp, † ‡ {masa, sezaki}@iis.u-tokyo.ac.jp

ABSTRACT

With the development of pervasive sensing by smartphone, we can now learn our society and surroundings better. Among all sensing information, the spatiotemporal data is extremely critical, consequently we suggest the way of trajectory sensing which record the sensor data combined with spatial position in order to perceive our lives and the real world. In this paper, we also conducted a series of trajectory sensing experiments through collecting ambient light and noise. Aside from the preliminary exploration of light and noise data along trajectory, we proposed a method to reduce the data volume of trajectory sensing.

Keywords: Trajectory Sensing, Light Sensor, Smartphone, Data Reduction, Microphone, Information Content.

1 INTRODUCTION

Smartphones or tablets are rapidly becoming the central computer and communication device in people's lives. The number of global smartphone users is expected to reach over 2 billion people by 2015 according to a report from market research firm Parks Associates. What's important, today's smartphones are programmable and come with a growing set of cheap powerful embedded sensors, such as accelerometer, light sensor, gyroscope, GPS, audio, Wi-Fi detector and camera. Exactly due to the pervasive mobile terminals and the development of sensors, recently a new research area called urban sensing or participatory sensing (also call opportunistic sensing) is emerged [1], which enables a different way to sense, learn, share information about our lives and the real word.

In this research area, researchers also explore the way of sensing from the viewpoint of data collecting. Thus, the idea like people-centric sensing [2] and human probe are currently suggested. On the other hand, thanks to current sensors and GPS technologies, trajectory of moving object (i.e. human, car, animals) can be obtained economically. People's trajectory is directly related to both their social activities and physical environment, subsequently the importance of spatiotemporal information is indubitable. Then, we believe that mobile sensing plus trajectory would open a new perspective of a broad spectrum of applications.

All mobile phones and tablets are equipped with ambient light sensor (ALS) and microphone. Usually ALSs are used to detect light or brightness so that these gadgets can automatically adjust in response to changing ambient light conditions, which can conserve battery power or eliminate the need for manual adjustments. And microphone in mobile phone initially serves as input of sound for communication. However, we intend to extend the basic function of these sensors to sense the ambient light and noise in our surroundings, which enables us to explore our community better.

Thanks to the development of smartphone and sensors, we now can collect large scale data by countless ordinary users. At the same time, the massive volume of data would hamper the further applications. Firstly, due to the limited memory of smartphone, the storage volume would become a problem. Secondly, the data obtained at mobile terminal is transmitted to a server in most sensing solution, i.e. PRISM platform [3]. Therefore, the communication cost of data transmission would increase in accordance with the volume. Finally, all the sensor data need to be analyzed for knowledge discovery; hence the huge volume would multiply the complexity of further data analysis.

Some tentative studies around aforementioned topics are introduced in this paper. The next section describes related work, and in section 3 we explain the concept of trajectory sensing. A series of trajectory sensing experiments including ambient light and noise is presented in section 4. We also devised an algorithm for data reduction in trajectory sensing in section 5. At the end, we discuss our proposal and experimental results as well as future work in the last section.

2 RELATED WORK

There is so much fruitful work in the literature of urban sensing even though it is newly emerged in recent years. J. Burke et al. performed a comprehensive survey of various applications in [1]. Although the data quality in participatory sensing is a primary concern and is considered as untrustworthy comparing with dedicated sensing station, S. Reddy et al. [4] evaluated the performance in participatory sensing and they presented a set of participation metrics along with a model to help organizers of sensing campaigns in order to ensure data accuracy. In fact, T. Horanont et al. [5] also developed a large-scale mobile sensing system to monitor urban, which prove the feasibility of participatory sensing. In addition, there has been a fair amount of work investigating multisensory mobile applications and services in recent years, such as urban planning [9, 19], activity recognition [20, 21], and health monitoring [22].

On the other hand, recently researchers are pursuing broader and better development of trajectory study. In the work of S. Spaccapietra [6] and L. Alvares [7], they attempt to attach rich contextual information on trajectory and then to boost location based services with semantic trajectory. They allow users annotate trajectory with POI information so that a basic trajectory (tuple of [x, y, t]) is extended to be semantic. However, their work just stay in geographical information along trajectory, and to our best knowledge, there are no studies to integrate environmental sensor data with trajectory. Thus, we will explore this topic in our study.

In the literature, there are a multitude of work [9, 19, 20, 21, 22] refer to embedded sensors of smartphone including accelerometer, gyroscope, Wi-Fi detector, GPS, etc. But there are only a handful of applications taking advantage of light sensor and sound sensor. Nevertheless, Rajib Rana et al. [8] and Prashanth Mohan et al. [9] fully utilized the microphone of smartphone to monitor environmental noise pollution and road condition respectively, which is meaningful. Another work on light sensor is to identify the object to acquire appropriate guidance in museum [10].

For the data reduction of trajectory, there exist various methods [11, 12] and Lawson et.al conducted a very comprehensive survey for them [13]. Most widely used methods are uniform sampling, dead reckoning method [14] and Douglas Peucker method [15]. Uniform sampling is to sparsely select the point to store every given time interval or distance interval but discards remained points. Dead reckoning method is a localized processing routine which make use of the characteristics of the immediate neighboring coordinate points in deciding whether to retain the current point. Douglas Peucker method recursively select two points to represent the line segment within a specified tolerance value. All the methods have the same goal – represent a trajectory by fewer sampling points with acceptable data loss. Regarding the measurement of data loss or error metrics, generally it is measured by distance, including the perpendicular distance and synchronized Euclidean distance.

3 TRAJECTORY SENSING

Trajectory is obtained by recording the successive positions of which a moving object takes across time. Generally, a trajectory consists of tuples (x, y, t), which keeps the spatiotemporal information. In most cases, the sensor data need to associate with the spatiotemporal attribute for further exploration. For example, it would be meaningless if the temperature, humidity, ambient light or noise data is gathered without the label of time and location. Moreover, people always engage in activities with movement, which naturally forms a complete trajectory. Let's back to the origin of participatory sensing or opportunistic sensing, it is exactly accompanied with participants' daily life. Therefore, it is undoubtedly seamless to combine trajectory tracking with participatory sensing (we call it trajectory sensing). Unlike spot sensing that dedicated sensors are set up in specific observation stations, trajectory sensing can gather more flexible, broader and of finer granularity data. Furthermore, a semantic trajectory would be extremely helpful as it involves in human social activities and takes sensor data of physical world into account.

More formally, trajectory T with sensing data can be defined as:

$$T = \{(X(t), Y(t), Z_*(t), Sm(t), t) | t \in I\}$$

Where $(X, Y, Z) \subset R^3$, $Sm \subset R^n$ and $Sm(t)$ represents other sensing data (i.e. noise, illumination) which vary along with trajectory over time.

We need to give an insight into the details of trajectory sensing, though the above conceptual definition can simply but fully encompass the nature of trajectory sensing. Although the finer the granularity of data is, the better we can perceive the environment, a certain type of data recorded in very position is too redundant. For example, temperature is not necessary to keep in every point of trajectory. Thus, we category sensor data into two types and summarize a logical scheme of trajectory sensing data relationship as figure 1. Considering the multi-granularity of sensing data, a trajectory is divided into multiple blocks, and sensing data of type 1 is associated with block but type 2 is associated with point. The entity of block is also a hierarchical structure which is similar to the topology of administrative area.

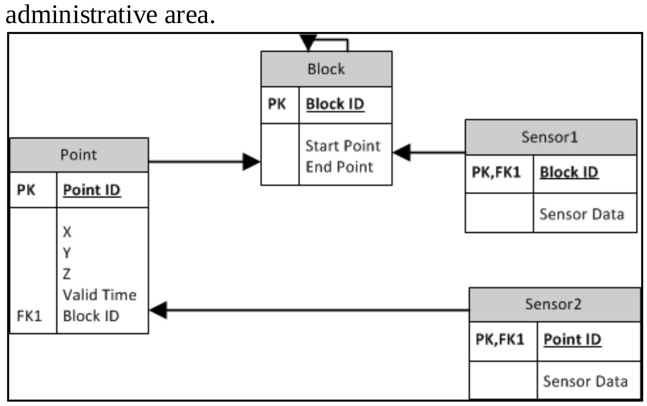

Figure 1: Scheme of multilevel trajectory sensing data

4 SENSING EXPERIMENTS

There is a wide variety of sensors equipped in smartphone, and android SDK support ten of sensors including accelerometer, ambient temperature, gravity, gyroscope,

Figure 3: Trajectory on Google map

light, magnetic field, orientation, pressure, proximity, relative humidity, etc. Aside from them, GPS, Bluetooth and Wi-Fi are also available. In our current experiments, we select GPS, ambient light sensor, microphone and accelerometer, and our focus is ambient light data.

Light sensor is among the simplest and cheapest sensors, and it is used to detect the intensity of light incident on a surface by measuring photoemission of visible light. It is measured in units called Lux. Table 1 shows the lux value in different light source. Light sensors are ubiquitous in modern society. Some applications use reflected light with optical detection for position sensing; these include bar code readers and laser printers. Other applications, such as digital cameras, cell phones and laptops, use optical sensors to gauge the amount of ambient light to adjust the screen's backlight to comfortable levels for the viewer. There mainly exist 3 types of light sensor with different accuracy and response time: photo resistor, photodiode, photo transistor. On smartphone the simplest one – photo resistor or photodiode is adopted, which is next to speaker in most models.

Table 1: Illuminance in different light source

Light Source	Illuminance (Lux)
Street Light	20
Dusk	1 to 200
Living Room	50 to 200
Office	200 to 600
Operating Room	5k to 10k
Cloudy	2k to 10k
Hazy	25k to 50k
Bright Sun	50k to 100k

*data source: from www.vishay.com

Microphone, which is used for conversation as an input of sound, is a basic component of smart phone. Developers can capture the data of sound volume and then convert it to sound intensity – decibel. Decibel (dB) is used to measure the loudness: it ranges from 50 to 60 dB in normal conversation, and about 70 db in busy street traffic.

To collect ambient light and noise along trajectory, we developed a tool based on Android (see figure 2). We conduct a series of experiments and collect the sensing data based on the definition of section 3. Here, Sm(t) includes accelerometer (x axis, y axis, z axis), latitude, longitude, illuminance and sound. The tool is tested on different gadgets, including HTC nexus one, Samsung nexus s, Motorola XT910, Samsung galaxy tablet, etc. We found it needs to calibrate in different models since the scale of value is variable according to specification, and Samsung nexus s and Motorola XT910 perform better in terms of light sensor.

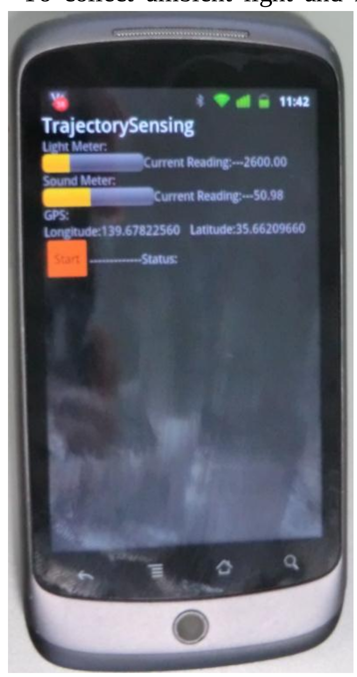

Figure 2: Trajectory sensing tool

We made some preliminary experiments from Komaba campus to Shimokitazawa station in Tokyo. Experiments are conducted at night by walking so that we can collect street lighting and facilities lighting. Figures 4, 5 and 6 show a part of our experimental data. Among them, figure 4 is ambient light along trajectory gathered by Samsung nexus s and figure 5 is gathered by Motorola XT910. Comparing with figure 3 which shows the corresponding trajectory of experiment on Google map, we can find that the active or bright part in figure 4 or 5 is exactly matched with the position of stations (Shimokitazawa Station and Ikenoue Station) and campus from left to right, which is inconsistent with our common sense.

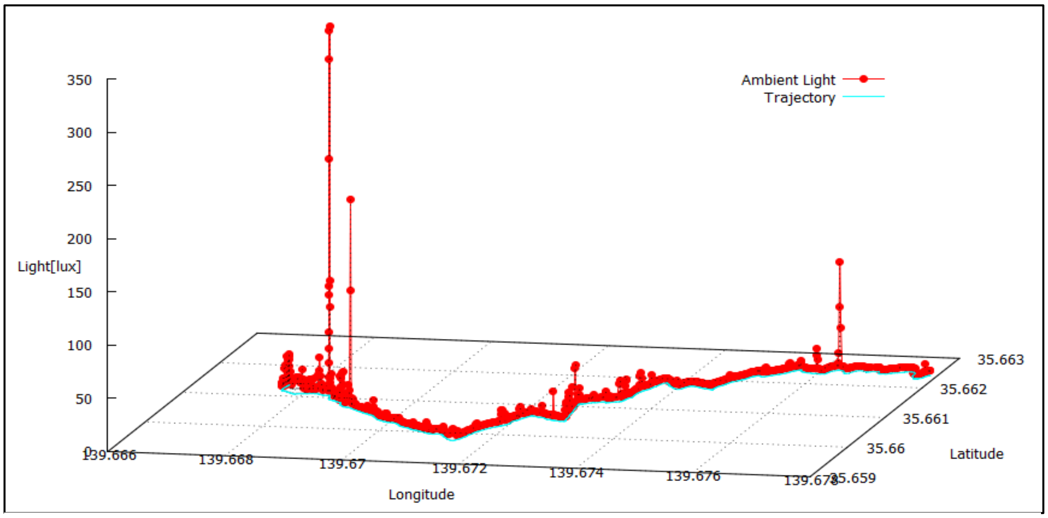

Figure 4: Ambient light along trajectory (Samsung nexus s)

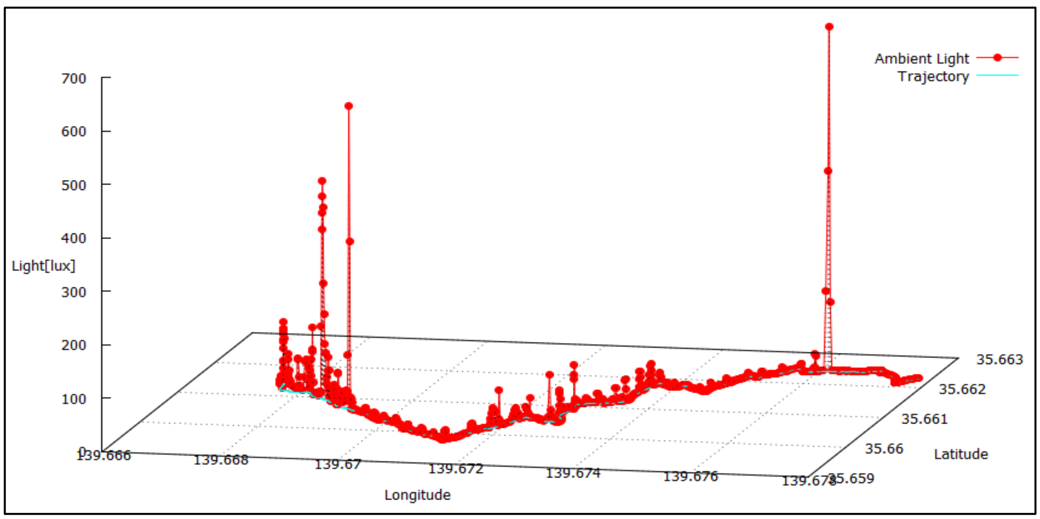

Figure 5: Ambient light along trajectory (Motorola XT910)

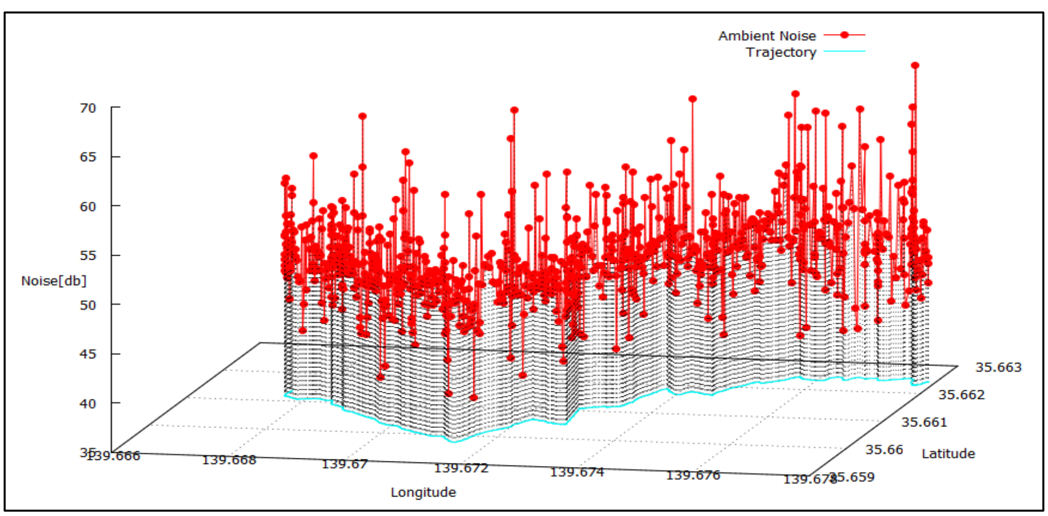

Figure 6: Ambient noise along trajectory (Samsung nexus s)

Besides, intermittent high-values also indicate the sparse street lights along the trajectory. As we see, figure 4 and figure 5 show the light of same trajectory at the same time, but the absolute value is variable. Therefore, it needs to take note that the calibration among different models should be done. Anyway, the data variance is nearly consistent so that we can utilize diverse models of gadgets to sense. Figure 6 also indicates that sound data is correctly recorded since it reflects the noise of real environment; however, it is difficult to read something only by this graph.

5 DATA REDUCTION METHOD

As stated previously, data reduction is extremely important. Although there are various compression methods for trajectory, they are not suitable for trajectory sensing because traditional trajectory compression methods merely place emphasis on keeping shape of trajectory. In trajectory sensing field, it is necessary to preserve both spatial information and sensing data.

5.1 Observation

Our method is derived from such an observation. In figure 7, there is a sample of sound data on which 3 MBRs (Minimum Bounding Rectangle) are drawn. In addition, we can conclude such assumptions by analyzing the information content of each range of sample data (see table 2):

(1) The bigger the area size of MBR of IC is, the more the sampling points should be stored (see MBR 2 in figure 7). Otherwise, we can omit more sampling points (see MBR 3).

(2) The sampling points on the boundary of MBR contain more information content (see the circled points in figure 7 and the corresponding IC value (with gray) in table 2).

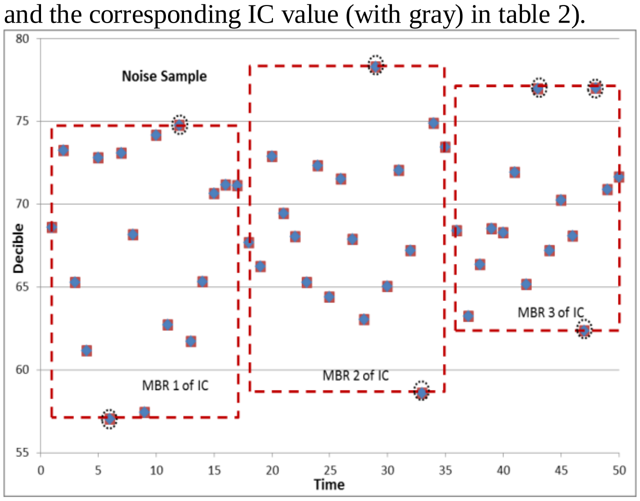

Figure 7: IC MBR on noise sample

Based on this observation, our purpose, to achieve the least data less, in other words, to keep the sum of information content as same as the original trajectory's counterpart, can be implemented. In a spatial trajectory, tuples of (x, y) can be seen as same as the data in that sample of sound data, since information content is reflected by the area of every group of sampling points and points on the boundary are more important. Next, two essential parts of our method are elaborated with an example of compressing spatial trajectory. Anyway, compressing sensor data can apply the same algorithm with slight modification.

Table 2: Information content of noise sample

Data Range	Information Content
55~60 db	-log(3/50) = 2.81
60~65 db	-log(7/50) = 1.97
65~70 db	-log(19/50) = 0.98
70~75 db	-log(18/50) = 1.02
75~80 db	-log(3/50) = 2.81
Sum	$\sum_{i=1}^{N} -\log(p_i) = 9.59$

5.2 Divide and Merge Principle

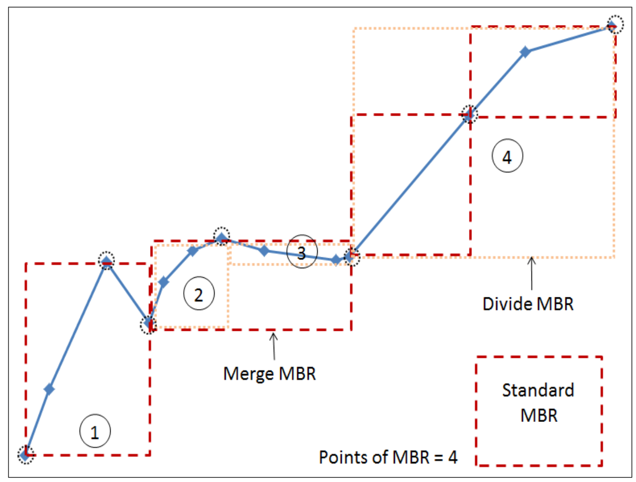

Figure 8: The illustration of IC_MBR method

Based on the first assumption stated in section 5.2, such a principle is applied, that we divide the bigger MBRs but merge the smaller MBRs so as to keep the nearly uniform size of MBR. There is an example shown in figure 8. Initially, 4 MBRs are drawn on it by every 4 points (the number is an input parameter specified by user), and then merge MBR 2 and MBR 3 because their area is far less than the standard MBR but split MBR 4 because it is far bigger than the standard MBR(the area is another input parameter). The size of the standard MBR can be obtained by user's experience or specific requirements. Another technique to determine an appropriate standard MBR (call adaptive MBR) is dynamically adjusting the value by calculating area size within a tuning period (i.e. take the median value of all MBRs). To keep the consistent accuracy, an adaptive MBR is more effective in the case of multi-transportation mode, since the area is subject to vary depending on walk mode or driving mode. Assume that the original sampling interval is a fixed time interval, standard MBR area is supposed to be assigned as a greater value in driving mode but a less value in walking mode. Hence, if the area or points number of standard MBR is dynamically programed with the consideration of both transportation mode and sampling interval, the result would be more satisfactory.

5.3 Selection Strategy

Through dividing or merging MBRs, every resulted MBR would contain the comparatively uniform information content. Hence, we apply such a strategy to extract points based on the second assumption stated in section 5.2. As shown in table 3 (call 4-2-1-0.5 rule), the points need to be stored is determined by comparison with the standard MBR area. For instance, select 4 points on boundary of MBR when the MBR meets condition 2 (see table 3), select the first point and the last point when meets condition 3, and select the median point when meets condition 4. In the case of the condition 5, if the MBR is a divided MBR then select the median point; or merge the MBR (which is explained in section 5.2 as well as rule 1).

Table 3: Points selection strategy

No	Condition	Selection Criteria
1	MBR(N) ⊂ [St_MBR * 2, ∞)	Divide MBR
2	MBR(N) ⊂[St_MBR, St_MBR * 2)	4 points; x(min), y(min), x(max), y(max)
3	MBR(N) ⊂ [St_MBR * 0.5, St_MBR)	2 points; x(0), x(N-1)
4	MBR(N) ⊂ [St_MBR * 0.25, St_MBR * 0.5)	1 point; x(median)
5	MBR(N) ⊂ [0, St_MBR * 0.25)	0.5 point; Merge MBR or x(median)

After integrating the divide/merge principle with the selection strategy, algorithm can be described as figure 8. This method adapts bottom-up and top-down strategy simultaneously, which recursively approximate line segments within a rectangle.

```
IC_MBR_Algorithm(St_MBR_Points_Num,
St_MBR_Area, Traj){
  Num = St_MBR_Points_Num;
  Foreach point in Traj{
    If Num = Buf.Count {
    rlt = SelectPoints(Buf);
    if rlt = false then Num = Num * 2; //Merge MBR
    }else{ Buf.Add(point);}
  }
}
SelectPoints(Buf){
  Area = (Max_X(Buf) – Min_X(Buf)) * (Max_Y(Buf) –
Min_Y(Buf));
  If Area > St_MBR_Area * 2{ //divide MBR
    SelectPoints(Buf/2); //first half of Buf
    SelectPoints(Buf/2); //second half of Buf
  }else if Area < St_MBR_Area / 4{
    Return false; //need to merge
  }else SavePoints(); //by selection strategy
}
```

Figure 9: The algorithm of our method

6 CONCLUSIONS AND FUTURE WORK

While there have been several sensing platforms that employ mobile phone or dedicated devices [16, 17], in this paper we propose a data model for trajectory sensing for the first time which is considered as more practical and more sensible. In addition, we conduct a series of experiments for collecting ambient light and noise along trajectory, and roughly analyze the sensor data. However, these sensing data especially ambient light are supposed to have further applications. (1) Light at night has a strong link with economic activities, so we can evaluate economic strength or status through illumination analysis. In fact, even in our preliminary study, we also can find that light nearby station is far brighter than residential area and the bigger the station is, the more and stronger the illumination is, while noise data behaves reversely. (2) It is helpful for safety route recommendation according to light condition and noise condition at night. While there is some significant work for personalized route planning with security consideration [18], they mainly focus on such security factors: road features, traffic accident rate and emergency response. However, for female travelers, they consider a bright and not-so-quiet path as safer when walking at night. (3) Moreover, indoor navigation or positioning is complicated due to failure of GPS, while light condition along trajectory probably opens a new door to it.

Last but not least, we present a new data reduction method which is universally efficient for both spatial trajectory and natural sensing data.

Currently we just successfully collected data and made preliminary analysis, in our later work, we will explore meaningful applications just as mentioned above. We also consider calibrating sensor data of illuminance by obtaining orientation and position of smartphone from accelerometer sensor.

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