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Indoor/Outdoor Detection for Seamless Positioning

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Abstract: Location-based Services are often required to cover indoor and outdoor environment, while indoor/outdoor detection for seamless positioning remains a longstanding challenge for Location-based Services. This paper presents an indoor/outdoor detection based on the variation of signals from multi-base stations. After study previous work, we put forward a new sampling algorithm, and then optimized signal intensity variation limit to improve the detection accuracy and decrease the time delay. With a large set of samples, we built a model based on the Naïve Bias algorithm on consideration that detection accuracy is related to the variation strength of cell station signals, which can be run with the initial state known. The indoor/outdoor detection, with accuracy up to 90 % and practically low energy consumption, is achieved. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Location-based Services, indoor/outdoor detection, Naïve Bias algorithm, GSM signal.

1. Introduction

As a strategic emerging industry, Location Based Services (LBS) have been widely applied in people's lives. In fact, mobile and wireless positioning techniques have attracted much interest and research recently, since they represent a core enabling technology for the continuously increasing number of mobile business applications based on LBS. Examples of these applications range from fleet management to fraud detection and from location-sensitive billing to network management. As its supporting technology, wireless location technology is supporting technology for LBS, whose development has been the most important determinant of LBS service quality [1].

Until now, the popular outdoor positioning technology is Global Positioning System (GPS), the Global Positioning System is a space-based global navigation satellite system that provides reliable location and time information in all weather and at all times and anywhere on or near the Earth when and where there is an unobstructed line of sight to four or more GPS satellites [2]. While, it is difficult to realize positioning when some blocks exists between the GPS receiver and satellite. So up to now, GPS is mainly used in outdoor positioning.

However, more than 80 % time of people's daily lives is in indoor environment. The requirement of indoor LBS is dramatically increasing. Indoor LBS is needed in fields such as special population care, key building management, internet of things and personal service. In the scenarios of emergency situations such as fire rescue and emergency evacuation, indoor location information becomes particularly important [3].

With the rapid development of short-range wireless networking technology, such as Wi-Fi

(Wireless Fidelity) and the growing popularity of mobile terminals, target positioning and tracking with these short-range wireless communications is becoming a hot research focus. These positioning technologies are easy to deploy and with low cost with the support of now widely deployed Wi-Fi infrastructure, and they are very suitable for applications in offices, workshops, schools, hospitals and other indoor environment [4].

In many cases, the services are based on indoor and outdoor location, such as location tracking services for the elderly, the blind, online community friends, as well as criminals and other suspects arresting. The seamless outdoor & indoor positioning system with Global Navigation Satellite System (GNSS) and ground network integration is evolving into significant strategy, and it is also becoming an important symbol of national capability [5]. While outdoor location can be achieved by GPS positioning, indoor location should be switched to positioning technology based on Wi-Fi, IP or Bluetooth signals. It is impossible to realize fast switching between positioning technology without indoor/outdoor knowledge, when a user is switching between indoor and outdoor environment. Based on the above analysis, indoor/outdoor detection plays an important role in seamless outdoor and indoor positioning systems.

Many location related work simply assume a clear pre-knowledge on the indoor/outdoor environment [3, 5]. In Reference 5, it deploys three optional indoor/outdoor locating solutions based on Multi-sensor, Satellite and Terrestrial positioning techniques, including Integrated GPS (Global Positioning System), Bluetooth GPS, AGPS (Assisted GPS), Network based, Multi-sensors, and Wireless LAN (WLAN), in order to cover indoor and outdoor environments, while it ignores how to transfer location signals between indoor and outdoor.

Current research on indoor/outdoor detection is very limited. Many works in this field are based on image processing and pattern recognition, which are not suitable for mobile applications, due to the amount of data needed to be calculated in mobile devices with limited calculation capacity [6, 7].

However, preliminary research work has been done in Reference 8, in which, an IODetector is presented as a lightweight sensing service which runs on the mobile phone and provides the indoor/outdoor environment detection. It works with light sensors, magnetism sensors, cell tower signals, etc. But the research is still in its infancy, its detection research is based on the experience value from limited experimental data, which cannot reach a practical level with sufficient reliability.

In this paper, we have tested the indoor/outdoor detection with magnetic signal received by the magnetic sensor. Due to its low accuracy, we exclude this technology. Indoor/outdoor detection with light sensor is also tested, the conclusion is that we can detect in daytime, but not in nighttime. While GSM signal testing shows significantly variation between indoor and outdoor environments, this paper mainly uses GSM signal to determine indoor and outdoor state.

The structure of the rest of this paper:

Section 2 gives relative research work on the indoor/outdoor detection based on cell signals. We do experiments with previous research work findings and find that detection accuracy needed to be improved and time delay needed to be decreased in Section 3. After that, in Section 4, we improve the sample interval, in Section 5, we optimize signal intensity variation to improve detection accuracy and decrease time delay. At last, we improve detection accuracy with Naïve Bias Classification Algorithnm on condition that indoor/outdoor dection accuracy is related to the strength of cell station signal variation.

2. Relative Works on Cell Station Signal Detection

In Reference 8, they utilize the significant variation of the cellular RSS (Received Signal Strength) when the ambient environment changes due to the user mobility. They exploit the abrupt variation of the cellular signal strength rather than its absolute value to distinguish the indoor/outdoor context that is invariant across different places and phone models. If a user moves from an indoor environment to an outdoor environment, the RSS of cell towers will increase, and vice versa. In addition, the more cell towers whose RSS variation exhibits the same trend, the more confident the detection will be. Therefore, instead of using the single associated cell tower, they take a full advantage of all visible cell towers to improve the detection accuracy.

They denote the RSS from cell tower *i* at time *t* as $R_i(t)$ $(1 \leq i \leq n)$; They track the RSS variation within a time interval Δ, and denote the variation of cell tower *i* as:

$$\mathrm{V_i(t) = R_i(t + \Delta) - R_i(t)} \tag{1}$$

They refer $\mathrm{N_+(t)}$ as the number of cell towers whose RSS increases more than ϑ:

$$\mathrm{N_+(t) = |\{i|V_i(t) \geq \vartheta, 0 \leq i \leq n\}|} \tag{2}$$

They also denote by $\mathrm{N_-(t)}$ as the number of cell towers whose RSS decreases more than ϑ:

$$\mathrm{N_-(t) = |\{i|V_i(t) \leq \vartheta, 0 \leq i \leq n\}|} \tag{3}$$

$$\frac{\mathrm{N_+(t) + N_-(t)}}{\mathrm{n}} \leq 1 \tag{4}$$

In their experiments, they set Δ = 10 sec, and ϑ = 15 dB.

3. Experiments for the Detection Accuracy and Time Delay with Previous Work

Indoor/outdoor detector should include three functions: detecting the switch between indoor and outdoor environment, stabilizing the indoor state in a disturbance of indoor RSS variations, and stabilizing the outdoor state in an opposite situation. The three functions were tested as follows:

Indoor/outdoor switch detection: We have tested indoor/outdoor switches at the entrances of many buildings, such as the entrances of teaching buildings, canteens and a gym in Beijing University of Posts and Telecommunications (BUPT), entrances of some supermarkets, restaurants and a subway station in Beijing. 1000 data have been received in our testing. The accuracy rate is 62 %, and the average time delay is 12 s.

Outdoor state stability: To test the outdoor state stability is to test the stability when the mobile phone is moving in an outdoor environment. We have tested it in our school playground, on streets, in buses for one day. There are over 50 errors.

Indoor state stability: To test the indoor state stability is to test the stability when the mobile phone is moving in an indoor environment. We have tested in many indoor environments, such as teaching buildings, dormitories, a gym, and many other buildings in BUPT and in Beijing in one day. There are about 30 errors.

In short, after testing in many places, we found that the detection accuracy needed to be improved and the time delay needed to be decreased, according to the detection method in Reference 8.

Fig. 1 shows the testing interface.

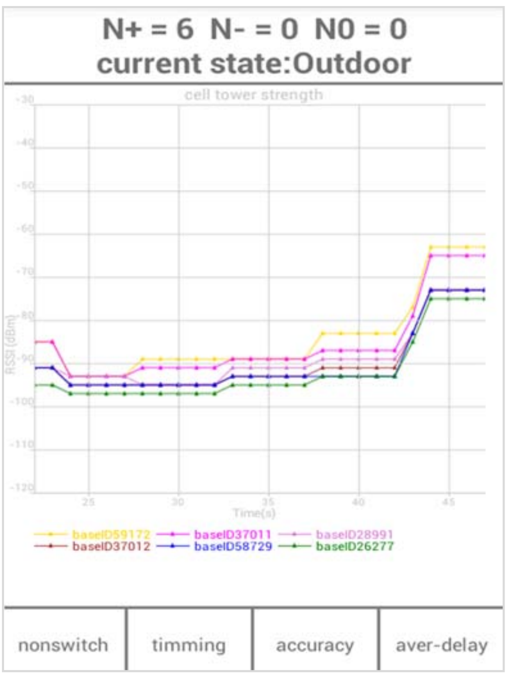

Fig. 1. Indoor/outdoor detection interface.

4. Sampling Algorithm Improvement and Implementation

4.1. Previous Sampling Algorithm

In Reference 8, the sampling time interval is 10 sec, they calculate RSS variation from any cell tower by comparing the RSS values at t_0+10i, and $t_0+10(i+1)$ on the time axis, e.g. $<(t_0+10i), (t_0+10(i+1))>$, i = 0, 1, 2, ...

The previous sampling algorithm is shown in Fig. 2.

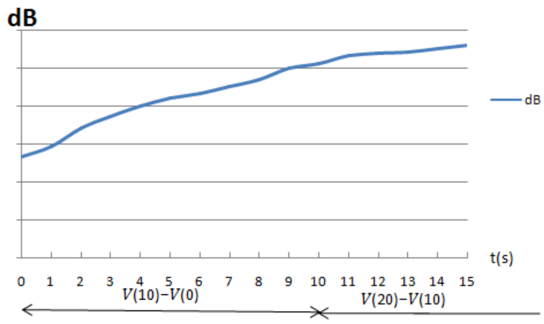

Fig. 2. Previous sampling algorithm.

4.2. Improved Algorithm

The sampling time interval is 1sec in the improved algorithm in this paper, from the eleventh second we calculate RSS variation by comparing the RSS values at t_0+j and t_0+j-10 on the time axis, e.g. $<t_0+j, (t_0+j-10)>$, j = 10, 11, 12, ...

The improved algorithm is shown in Fig. 3.

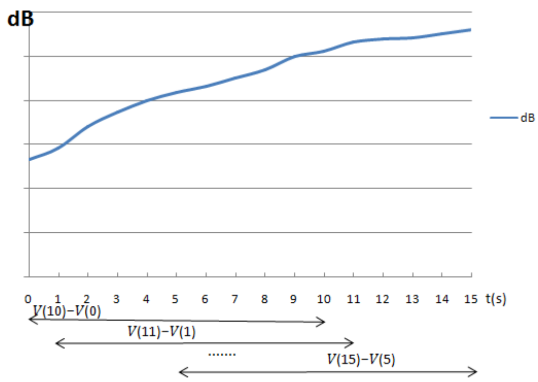

Fig. 3. Improved algorithm.

From Fig. 3, we can see that in 15 seconds, we can sample up to 5 times for detection with our improved algorithm, while only no more than 1 time with the previous algorithm.

In our indoor/outdoor switch detection testing, the improved algorithm not only can improve test accuracy apparently, but also can solve the time delay problem in the indoor/outdoor detection.

5. Finding Optimal Signal Intensity Variation Limit to Improve Detection Accuracy and Decrease Time Delay

The original test is based on the signal intensity variation limit ϑ = 15 dB, we change the value of ϑ, into 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, …, 18 dB. Detection accuracy and time delay varying with the intensity variation limit is shown in Fig. 4.

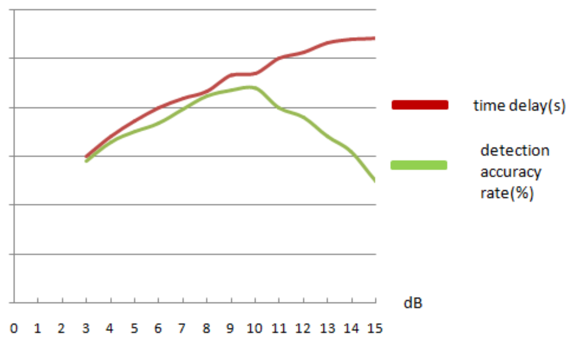

Fig. 4. Detection accuracy and time delay with the intensity variation limit ϑ.

From Fig. 4, we can see that on the detection accuracy curve, the optimal ϑ for detection accuracy is around 10 dB. Time delay is proportional to ϑ. We can set ϑ = 10 dB for optimal detection accuracy, and the time delay is about 8 seconds.

6. Improving Detection Accuracy with Naïve Bias Classification Algorithm

The Bias Classification represents a supervised learning method as well as a statistical method for classification. Assumes an underlying probabilistic model and it allows us to capture uncertainty about the model in a principled way by determining probabilities of the outcomes. It can solve diagnostic and predictive problems.

The formal definition of the naïve Bias:

1. Suppose that
$x = \{a_1, a_2, \dots, a_m\}$,
$a_i(\, i = 1, \dots m)$ is one of attributs of x.
2. Class set is
$C = \{y_1, y_2, \dots, y_n\}$
3. Calculating
$P((y_1|x)), P((y_2|x)), \dots P((y_n|x))$.
4. If $P(y_k|x) = \max\{P(y_1|x), P(y_2|x), \dots, P(y_k|x)\}$, then $x \in y_k$.

We can do it as follows:

1. Find a set of data to be classified. The set is named training sample set.

2. Calculate conditional probability estimation of all attributes for each class.

$$P(a_1|y_1), P(a_2|y_1), \dots, P(a_m|y_1),$$
$$P(a_1|y_2), P(a_2|y_2), \dots, P(a_m|y_2),$$
$$\dots \dots$$
$$P(a_1|y_n), P(a_2|y_n), \dots, P(a_m|y_n)$$

3. If all the attributes are conditionally independent, then according to the Bias theory, the deduction formula is as follows:

$$P(y_i|x) = \frac{P(x|y_i)P(y_i)}{P(x)} \tag{5}$$

4. Because the denominator for all class is constant, we only need to maximize the molecular. Because each attribute is independent, we can deduct:

$$P(x|y_i)P(y_i) = P(a_1|y_i)P(a_2|y_i) \dots P(a_m|y_i) \tag{6}$$

Set that V=1 represents an indoor/outdoor switch, while V=0 represents no indoor/outdoor switch:

1. Determine feature attributes

We denote the RSS from cell tower *i* at time *t* as *Ri(t)*, $1 \le i \le n$; We track the RSS variation within a time interval Δ = 10sec and denote the variation of cell tower *i* as: t_0+j, (t_0+j-10), j = 10, 11, 12, ... So, Equation (1) is changed into Equation (7) as follows:

$$V_i(t) = R_i(t + j) - R_i(t + j - 10) \tag{7}$$

According to our study in Section 5, we set ϑ = 10 dB in Equation (2) and Equation (3).

We refer a as the difference between $N_-(t)$ in Equation (3) and $N_+(t)$ in Equation (2).

$$a = N_-(t) - N_+(t) \tag{8}$$

$$b = \frac{1}{n}\sum_{i=1}^{n} V_i(t) \tag{9}$$

Initial state includes indoor state and outdoor state. Here we only illustrate the detection based on an indoor initial state.

i. dividing *a* into value ranges:

$\{a \le 0, 0 < a \le 2, 2 < a \le 6, 6 < a\}$;

We refer *b* as the average value of signal intensity variation from all cell towers. We divide it into value ranges: $\{b \le -10, -10 < b \le -5, -5 < b \le 5, 5 < b\}$;

ii. getting training sample set

Obtain training sample set with 2000 data by human judgment which is shown in Table 1.

iii. Calculating probability of each category in the sample training set

P(V=1)=200/2000=0.1

P(V=0)=1800/2000=0.8

Table 1. Sample data distribution on attribute *a*.

	V=0	V=1
$a \le 0$	1034	3
$0 < a \le 2$	834	10
$2 < a \le 6$	134	177
$6 < a$	15	10
total data	1800	200

Table 2. Sample data distribution on attribute *b*.

	V=0	V=1
$b \le -10$	69	22
$-10 < b \le -5$	331	110
$-5 < b \le 5$	910	58
$6 < a$	690	10
total data	1800	200

iv. Obtaining conditional probability of each attribute in the training set

P($a \le 0$|V=0)=0.5733;
P($0 < a \le 2$|V=0)=0.417;
P($2 < a \le 6$|V=0)=0.067;
P($5 < a$ |V=0)=0.0075;
P($a \le 0$|V=1)=0.015;
P($0 < a \le 2$|V=1)=0.05;
P($2 < a \le 6$|V=1)=0.885;
P($5 < a$ |V=1)=0.005;
;
P(b ≤ -10|V=0)=0.0383;
P($-10 < b \le -5$|V=0)=0.1839;
P($-5 < b \le 5$|V=0)=0.5056;
P($5 < b$ |V=0)=0.3833;
P(b ≤ -10|V=1)=0.11;
P($-10 < b \le -5$|V=1)=0.55;
P($-5 < b \le 5$|V=1)=0.29;
P($5 < b$ |V=1)=0.05;

v. Identifying indoor/outdoor detection

For example, we have test attributes of x as: *a*=3, *b*=5db

P(V=0)P(x|V=0)
=P(V=0)P($2 < a \le 6$|V=0) P($-5 < b \le 5$|V=0)=0.8*0.067*0.5056=0.0271
P(V=0)P(x|V=1)
=P(V=0)P($2 < a \le 6$|V=1) P($-5 < b \le 5$|V=1)=0.2*0.885*0.29=0.05133
So because
P(V=0)P(x|V=0)< P(V=0)P($2 < a \le 6$|V=1)
The detection result is IO switch.

8. Evaluation

We implement a prototype system on the Android platform with 3 different types of mobile phones. We collect 4000 data from different sites in Beijing University of Posts and Telecommunications and Beijing, among of them, 1500 are collected from outdoor environment, 3500 are from indoor environment.

Fig. 5 shows the testing interface on Android Platform.

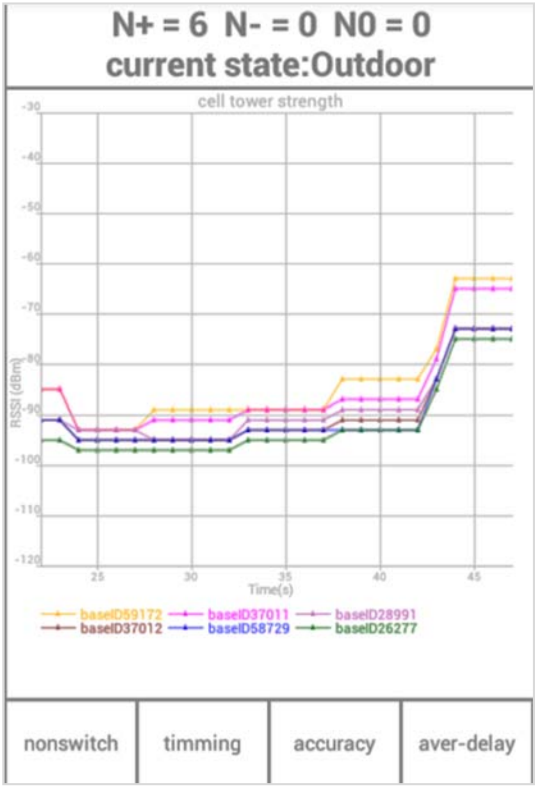

Fig. 5. Indoor/outdoor detection interface.

8.1. Detection Accuracy

Detection accuracy is shown in Fig. 6.

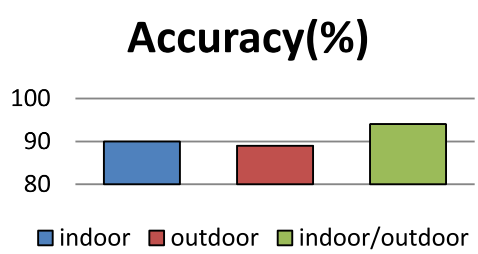

Fig. 6. Detection Accuracy.

8.2. Detection Latency

The detection latency is about 7 sec when we detect indoor/outdoor switch.

8.3. Energy Consumption

We have measured the battery duration by comparing our detection application on and off. Our indoor/outdoor detection is very energy savable, the reason of which is that mobile phones have to maintain connectivity to cell towers for basic communication all the time.

9. Summary

This paper presents an indoor outdoor detector based on variation of signals from multi base stations. We improved the sampling algorithm, and then optimized signal intensity variation limit to improve the detection accuracy and decrease the time delay. With a large set of samples, we built a model based on the Naïve Bias algorithm, which can be run with the initial state known. The indoor/outdoor detection, with accuracy up to 90 % and practically low energy consumption, is achieved.

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