Research on Library Seat Resource Monitoring Technology Based on Mobile Crowdsensing (Postprint)

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Abstract

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Full Text

Preamble

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Research on Monitoring Technologies for Library Seating Resources Based on Mobile Crowdsensing

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Abstract

[**Purpose/Significance**] Efficient monitoring and management of library seating resources has long been a challenging problem for universities. Existing approaches primarily rely on deploying dedicated hardware and software systems, which suffer from high costs, difficult maintenance, and poor user experience. This study proposes a novel low-cost and easily maintainable technology for library seating resource monitoring and management. [**Method/Process**] Leveraging the concept of mobile crowdsensing, combined with indoor localization and context-aware technologies, we developed a cost-effective and user-friendly seating resource monitoring technique and implemented a demonstration system using WeChat Mini Program as the platform. [**Result/Conclusion**] The results demonstrate that this technology is low-cost, easy to deploy, and capable of efficiently monitoring and managing library seating resources.

Keywords: mobile crowdsensing; library seating resource management; indoor localization; WeChat Mini Program
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Efficient monitoring and management of library seating resources has been a persistent challenge for universities. As modern university libraries continue to expand in scale and area, the problem of uneven seat utilization has become increasingly pronounced—some reading rooms are overcrowded while others remain largely vacant. Students often waste considerable time and effort searching for available seats, squandering valuable study time. For library administrators, many seats remain idle for extended periods, representing a significant waste of resources. A viable solution involves real-time monitoring of seat usage across various reading rooms, enabling rational allocation of seating resources and guiding students to designated reading rooms based on availability.

2. Literature Review

The problem of library seat monitoring and management has existed for years, with issues such as seat hogging and non-compliant usage occurring frequently. Libraries have continuously sought solutions, with current approaches focusing on precise per-seat management—assigning specific seats to individual students. Existing seat monitoring methods fall into two main categories: (1) hardware-based recognition, such as using infrared [1] or RFID [2] devices to precisely detect occupancy and assign seats; and (2) software-based reservation systems [3] that allocate seat numbers to students. Both approaches have significant drawbacks. Hardware-based methods entail extremely high deployment and maintenance costs and still require backend software support. Software-based approaches necessitate user training and rely heavily on user compliance; many users bypass the system entirely and sit directly, increasing management difficulty.

Specifically, lower-cost software solutions have been implemented at institutions such as Tsinghua University [3], Xiamen University [4], and Shenzhen University [5], where students must apply for seat usage through software before entering, sit according to assigned numbers, and manually check out or wait for automatic timeout upon leaving. The flaw in this scheme is its inability to verify actual compliance—for instance, when students leave early without checking out, the system fails to release the seat, causing resource waste. To address this, some libraries use campus card swiping to track entry and exit, as implemented at Tsinghua University [3] and Harbin University of Science and Technology [6], though missed swipes occur frequently. For precise occupancy detection, another approach involves deploying additional hardware recognition devices within libraries. Researchers at Southeast University utilized infrared proximity detection [1] to determine seat availability, while Anhui Normal University combined infrared and RFID [7] to identify exactly who sits where. However, such solutions involve prohibitive deployment and maintenance costs, making large-scale implementation impractical. Another limitation of existing technologies is the need to train students and staff on software operation after system deployment, requiring all users to follow prescribed procedures for seat allocation and usage. While these two categories of methods can functionally manage seating resources, they still lead to conflicts. In practice, even with seat management systems in place, incidents of students occupying others' seats or not following assigned seating persist, often requiring librarian intervention and increasing both workload and management confusion.

Mobile crowdsensing [8] is an emerging concept in mobile computing in recent years. The core idea leverages the collective intelligence of large user populations, enabling unconscious participation to complete sensing and computing tasks that would otherwise require significant professional effort. Crowdsensing shares similarities with crowdsourcing in implementation and philosophy. Crowdsourcing, a term originating from the United States to describe a new production organization model, involves distributing work and solving problems through networks. In computer science, this concept has found extensive applications in popular fields such as artificial intelligence, big data, and IoT, with widespread research in environmental monitoring [9], traffic surveillance [10], and security management [11]. The core principle of crowdsensing is utilizing the unconscious participation of numerous users to accomplish tasks that would otherwise be costly, with smartphones—possessing strong sensing, computing, and communication capabilities—serving as the primary tool. This work applies mobile crowdsensing technology to real-time occupancy information collection for library seating resources, fully leveraging its advantages to drastically reduce hardware and labor costs. To our knowledge, no prior research has applied this technology to library seat management.

Mobile crowdsensing can infer reading room occupancy rates using only the smartphones of existing users within the room. This requires first identifying which reading room the user is in, necessitating user localization. This study employs Wi-Fi fingerprint-based indoor localization technology to determine reading room location. The earliest and most classic scheme was implemented by P. Bahl et al. based on the RADAR [12] algorithm, which first proposed using Wi-Fi signals as location fingerprints. Numerous improved algorithms followed, such as Horus [13], ActiveCampus, PlaceLab [14], and OIL. These schemes target specific coordinate positions with accuracy evaluated in centimeters or meters—for example, Horus improved upon RADAR's K-nearest neighbor deterministic matching strategy, achieving indoor precision within 10 meters. However, our application differs: we only need to identify which reading room the user is in, with accuracy evaluated simply as correct or incorrect. Therefore, we redesigned and improved the Wi-Fi fingerprint-based localization algorithm to better suit this specific scenario.

3. Seat Resource Monitoring Technology Design

Accurately determining occupancy rates for each reading room without relying on additional specialized hardware is technically challenging. Our approach fully utilizes the sensing and computing capabilities of smartphones already present among students in the reading room. Specifically, through mobile crowdsensing technology, the system obtains sensing data from participating students' phones, such as surrounding Wi-Fi and Bluetooth device IDs and signal strengths. Using Wi-Fi fingerprint-based indoor localization, the system identifies which reading room the student is in, then applies our proposed Bluetooth context-based occupancy inference algorithm to deduce the room's occupancy rate and assign seats to incoming students. This section first introduces the overall technical architecture, then details the design and implementation of each technical module.

3.1 Technical Architecture

Our seat resource monitoring technology comprises three layers from bottom to top (see Figure 1 [Figure 1: see original paper]): (1) The bottom layer is the mobile crowdsensing layer, which collects sensing data from participating students' smartphones, including IDs and signal strengths of surrounding Wi-Fi and Bluetooth hotspots; (2) Above it is the recognition layer, which uses this data to determine the specific reading room where the student is located and infers the room's occupancy status through inference algorithms; (3) The top layer is the application layer, which dynamically assigns seats to newly arriving students based on real-time occupancy across all reading rooms, thereby achieving dynamic seat resource management.

3.2 Mobile Crowdsensing Technology

In our application scenario, the crowdsensing-based approach offers significant advantages over traditional methods requiring extensive specialized equipment to identify occupancy rates. Sensing data previously provided by professional devices can now be obtained through crowdsensing. The physical layer uses participating students' smartphones or tablets as sensing devices, running a crowdsensing client that is ultimately integrated as a small software module within the seat resource monitoring system (embedded in the WeChat Mini Program demonstration system). This program automatically runs in the background, collecting and transmitting data via the library's free network to cloud servers for use by the recognition layer's localization and occupancy inference algorithms. Throughout this process, students need not manually operate their phones; they naturally perform sensing and data upload while studying in the reading room, providing excellent user experience.

3.3 Wi-Fi Signal Fingerprint-Based Location Recognition Technology

Wi-Fi fingerprint-based localization is a widely used indoor positioning technology that only requires smartphones to sense multiple surrounding Wi-Fi hotspots' IDs and corresponding Received Signal Strength (RSS). Through signal fingerprint matching algorithms, user location can be determined with general precision within five meters. This technology requires no additional positioning equipment, offers low cost, and is easy to deploy. In our scenario, the system only needs to identify which reading room the user is in.

System deployment consists of two phases: training and operation (see Figure 3 [Figure 3: see original paper]). The training phase involves site surveys to pre-collect Wi-Fi signal fingerprints for each library reading room and store them in a cloud database called the reading room fingerprint database. The operation phase performs real-time localization by having users' smartphones collect surrounding Wi-Fi signal fingerprints and providing them to the localization algorithm, which finds the closest match from the fingerprint database through a specially designed matching algorithm to identify the user's current reading room.

For the core fingerprint matching algorithm, we employ the K-Nearest Neighbors method (typically with K > 1). First, we calculate the RSS distance between real-time collected samples and average RSS values in the fingerprint database, then identify the nearest fingerprints. The target location (x, y) is computed as the center position of these k locations:

$$(x, y) = \frac{1}{k} \sum_{i=1}^{k} (x_i, y_i)$$

where (x_i, y_i) are the coordinates of the k nearest fingerprints. However, unlike traditional KNN, our requirement is reading room-level accuracy rather than precise coordinates, making standard KNN implementation suboptimal. Additionally, real-time fingerprint lists may not share common hotspots with the nearest stored fingerprints, even when physically close. Therefore, we customized the algorithm by analyzing the reading rooms corresponding to the k nearest fingerprints and selecting the most frequently occurring reading room as the final result. This approach is based on the assumption that Wi-Fi hotspot signal strengths scanned by smartphones vary significantly between reading rooms—a hypothesis consistent with actual Wi-Fi signal characteristics, as verified by experimental results.

3.4 Bluetooth Context-Based Occupancy Inference Algorithm

Through mobile crowdsensing and Wi-Fi fingerprint-based indoor localization, the system obtains crowdsensing data from participants in specific reading rooms. This algorithm uses Bluetooth sensing data to infer the room's occupancy rate. Bluetooth devices on participants' phones can scan IDs and signal strengths of other Bluetooth devices in the environment, helping count nearby users with Bluetooth enabled. Importantly, not all users in the reading room need to participate—only a minimal number of participants is required.

Current smartphones primarily use Bluetooth 4.0 communication protocol with a standard transmission range of 100 meters, though this is significantly reduced in indoor environments, and Bluetooth signals rarely penetrate walls. This property enables counting users within a reading room without mistakenly including users from adjacent rooms. The algorithm proceeds as follows: (1) Aggregate Bluetooth devices scanned by participants in the reading room by ID, removing duplicates while retaining higher signal strength data; (2) Remove Bluetooth devices with signal strength below a threshold (-90 dBm), as low-strength devices are likely in other reading rooms. The resulting ID count represents the number of users with Bluetooth enabled in that reading room.

Since the algorithm's goal is to obtain the total user count to calculate occupancy rate, knowing only the number of Bluetooth-enabled users is insufficient. We designed a user count prediction formula (Equation (3)) that estimates actual user numbers from Bluetooth user count:

$$M = \frac{N}{\phi}$$

where ϕ is the estimated Bluetooth enablement rate, M is total users, and N is Bluetooth-enabled users. The simplest approach sets ϕ as a constant (e.g., 80% or 70%), but this is subjective and may not reflect reality. Our solution combines historical and real-time data to determine ϕ, as shown in Equation (4):

$$\phi = \phi' \times \alpha + \frac{\sum N_i}{M_{all}} \times (1 - \alpha)$$

where ϕ' is the historical average (over one week) of ϕ, α is the historical data weight coefficient (0 to 1), ΣN_i is the sum of Bluetooth-enabled users across all reading rooms, and M_{all} is the total library student population obtainable from the library card system. Occupancy rate   is then calculated as:

$$\rho = \frac{M}{S_i}$$

where S_i is the known seat count for the reading room. Regarding α determination, the system default is 0.5, giving equal weight to historical and real-time data. However, when M_{all} is less than 20% of reading room capacity, real-time enablement data becomes less accurate due to sparse occupancy, and α is set to 1.

3.5 Seat Recommendation and Management

Traditional seat management assigns fixed seats to users, which, as previously noted, involves complex operations and creates problems such as seat hogging and non-compliance. Our approach recommends reading rooms rather than specific seats, allowing users to choose based on their needs. Since the system obtains real-time user counts for each reading room, it naturally knows the availability of seats in each room. When users enter the library, the system recommends 3-5 suitable reading rooms on the interface, displaying specific availability for each. Users select their preferred reading room, and as people enter and exit, availability updates in real time without requiring complex seat selection or checkout operations.

3.6 Summary

Our technical approach can be summarized as: Through mobile crowdsensing, the system obtains sensing data from participating users' phones; using Wi-Fi fingerprint-based indoor localization, it identifies participants' reading rooms; through our Bluetooth context-based occupancy inference algorithm, it deduces each reading room's occupancy rate; finally, it guides incoming students to reading rooms based on real-time occupancy, achieving seat recommendation and management. At the user level, the entire process requires no hardware or software operation from students or administrators, greatly reducing complexity. At the system level, deployment and operation require no specialized hardware or dedicated maintenance staff, significantly reducing costs.

4. System Implementation

Based on the algorithms proposed in Section 3, we implemented a demonstration system for library seat resource monitoring using WeChat Mini Program as the platform. The system configuration is as follows: (1) Programming languages: Frontend uses HTML5 + JavaScript, web server uses Java Servlet, core algorithms implemented in Java; (2) Runtime environment: Server OS uses Windows 2003, web server uses Tomcat 5; client runs in WeChat Mini Program environment; (3) Database: MySQL 5.6.

4.1 Interface Definitions for Seat Resource Management

Crowdsensing data acquisition, user localization, reading room population estimation, and seat recommendation were all implemented as independent interfaces exposed as web services for application logic invocation. Due to space limitations, key interfaces are listed below:

(1) **Crowdsensing Data Acquisition Interface**
Function: Obtain crowdsensing data from participating users.
Definition: `List<CcData> crowdsing(string roomId, int n)`
Input: Reading room ID, time period (seconds).
Output: User crowdsensing data from the reading room within the past n seconds.

(2) **User Location Recognition Interface**
Function: Identify the reading room where the user is located.
Definition: `Location getLocation(WiFiList sample, int k)`
Input: Current user's surrounding Wi-Fi signal strength data sample, k value.
Output: User's current location.

(3) **Reading Room Population Calculation Interface**
Function: Calculate reading room population from crowdsensing data.
Definition: `int inferUserNum(List<CcData> list, $\phi$)`
Input: Crowdsensing data for the reading room, ϕ value.
Output: Number of people in the reading room.

(4) **Seat Recommendation Interface**
Function: Recommend seats to users based on occupancy across all reading rooms.
Definition: `List<Room> recRooms(List<Room> m, int n)`
Input: Occupancy status of all reading rooms, number of rooms to recommend.
Output: List of recommended reading rooms (n rooms).

4.2 Bluetooth-Based Occupancy Inference Implementation

Based on the design in Section 3.4, the algorithm first obtains the number of Bluetooth-enabled users in the reading room through crowdsensing, then calculates the total user count using the current ϕ value. The pseudocode is as follows:

```
Algorithm: inferUserNum
Input: list (crowdsensing data), $\phi$ (Bluetooth enablement rate)
Output: M (estimated total users)
1. Initialize empty set S
2. For each crowdsensing data d in list:
3.   For each Bluetooth device b in d:
4.     If b.signal > -90 dBm:
5.       S.add(b.id, b.signal) // Keep higher strength if duplicate
6. N = size of S
7. M = N / $\phi$
```

```
8. Return M
```

4.3 Wi-Fi Fingerprint Localization Implementation

The improved Wi-Fi fingerprint localization algorithm calculates the k nearest fingerprints based on the distance formula from Section 3.3, analyzes these fingerprints, and selects the most frequently occurring reading room as the output. The pseudocode is as follows:

```
Algorithm: getLocation
Input: sample (Wi-Fi signal list), k
Output: location (reading room)
1. Initialize min-heap H
2. For each fingerprint f in database:
3.   dist = calculateDistance(sample, f)
4.   H.push(dist, f)
5. Initialize map roomCount
6. For i = 1 to k:
7.   f = H.pop()
8.   roomCount[f.room]++
9. Return room with max count in roomCount
```

4.4 Seat Recommendation Implementation

Based on the design in Section 3.5, the system randomly recommends 3-5 candidate reading rooms according to current occupancy rates. Different users may receive different recommendations; rooms with higher availability have higher priority. The algorithm aims to balance load across all reading rooms. The pseudocode is as follows:

```
Algorithm: recRooms
Input: m (list of rooms with occupancy), n (number to recommend)
Output: list of n recommended rooms
1. Sort m by occupancy rate ascending
2. Return top n rooms from sorted list
```

4.5 WeChat Mini Program Implementation

The user terminal is implemented as a WeChat Mini Program, which offers simple development and powerful functionality. The mini program enables crowdsensing data acquisition, including Bluetooth and Wi-Fi signals. The interface is developed using HTML5, and WeChat's built-in user authentication eliminates complex user profile management. Most system processing occurs in the mini program backend and web server, requiring no complex user operations. Users simply open the mini program, which displays 3-5 currently available reading rooms and shows the user's real-time location without additional manual input. User status and reading room availability update automatically. Users willing to participate in crowdsensing simply check a corresponding option, and participating users receive reward points redeemable for prizes. The interface is shown in Figure 4 [Figure 4: see original paper].

5. System Experiments

To validate system effectiveness, we conducted tests at the Jiulonghu Library of Southeast University. The experimental setup was as follows: (1) Four study rooms on the library's first floor were selected as the test scenario: rooms A201, A208, B201, and B206, with seat counts and locations shown in Figure 5 [Figure 5: see original paper]; (2) Wi-Fi location fingerprints for these four rooms were manually collected to establish a fingerprint database; (3) Reading room information was entered into the system, including room numbers and corresponding seat counts.

At the start of the experiment, several students were randomly selected in each study room to participate in crowdsensing (simply by opening the WeChat Mini Program). The experiment lasted 7 hours, from 9:00 AM to 4:00 PM. Before entering a study room, students could see the system interface on entrance screens, which displayed available reading rooms sorted by availability, allowing them to choose freely. During the experiment, actual room occupancy was manually counted every hour, and participants' locations and account information were recorded. Simultaneously, the system's localization records and real-time population data for each room were logged on the server. Post-experiment comparison between manual records and system data yielded the following results:

(1) **Student Localization Accuracy**. Figure 6 [Figure 6: see original paper] shows localization accuracy across the four reading rooms. For instance, in room A208, 60 localizations were performed with 58 correct and 2 errors (both misplacing users in adjacent room B206). The overall reading room localization accuracy was 98%.

(2) **Reading Room Population Calculation Accuracy**. Figure 7 [Figure 7: see original paper] shows the difference between calculated and actual populations throughout the experiment, displaying average, minimum, and maximum error rates. For room A208, the average error rate was 6%, with maximum and minimum errors of 14% and 3%, respectively. The overall average error across all reading rooms was 6.8%. Experiments indicate that error gradually decreases as the number of participating users increases. Figure 8 [Figure 8: see original paper] compares actual and estimated populations for room B206 across time periods, showing close alignment. Error rates showed little difference between low and high occupancy scenarios. Population estimation errors stem primarily from two factors: deviation in the estimated Bluetooth enablement rate ϕ, which varies over time as it depends on dynamically determined real-time data, and uneven distribution of crowdsensing participants, causing some bias in detecting all Bluetooth-enabled users nearby.

(3) **Seat Recommendation Effectiveness**. This comparative experiment examined occupancy distribution between the four rooms using seat recommendations and four rooms on the second floor without recommendations. As shown in Figure 9 [Figure 9: see original paper], the results demonstrate that the four rooms with seat recommendations achieved more balanced occupancy distribution compared to those without recommendations.

6. Conclusion

This paper proposes a seat resource monitoring technology based on mobile crowdsensing. The fundamental concept involves obtaining sensing data from reading rooms through crowdsensing, then using our Bluetooth context-based occupancy inference algorithm to identify room population and seat usage. This solution requires no additional hardware deployment or maintenance, achieving extremely low cost. The software runs automatically in the background without user operation, minimizing user burden. The technology leverages hardware recognition advantages while avoiding high hardware costs, combining software techniques to make significant progress in efficiently monitoring and managing library seating resources. We implemented a demonstration system on WeChat Mini Program and validated its effectiveness through field testing. Future work will improve population calculation accuracy and conduct larger-scale tests to enhance system usability and reliability.

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Research on Monitoring Technologies of Library Seating Resources Using Mobile Crowdsensing

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Abstract: [Purpose/significance] This paper studied how to efficiently use the seat resources of libraries, and proposed low cost and easy to maintain technologies for seat resources management. The existing approaches are mainly based on deploying related hardware and software systems. Such methods are expensive, difficult to maintain, and with poor user experience. [Method/process] With the help of mobile crowdsourcing, the paper used technologies such as indoor location and context aware, and proposed a seat resources management technique framework. The system was realized using WeChat application and evaluated under real situations. [Result/conclusion] The result showed that the technology has low cost and easy to deploy, and great progress has been made for the problem of efficiently using the seat resources of libraries.

Keywords: mobile crowdsourcing; seat resources management in libraries; indoor localization; WeChat application

Note: Figure translations are in progress. See original paper for figures.