A Novel Architecture for Radio Environment Map Construction Based on Mobile Crowd Sensing

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1. Introduction

It is with great significance to improve the utilization of radio resources. In order to characterize the situation of radio resources timely and accurately, it is necessary to understand the radio information and share it with some applications. Radio Environment Map (REM) is such a feasible system, which covers a large scale of radio environment information, such as available spectrum, geographic information, strategy, geographical features, available services, spectrum regulations, locations and activities of radios, relevant policies and past experiences [1]. Based on these information, further details of the radio environment can be measured, modeled, and then applied to a variety of upper-layer applications.

Currently, most of the REMs aim at small-scale applications. The universal methods to build a REM are deploying sensors in a certain environment to collect the sensing data. The REM is applied to different kinds of networks and applications, which requires the networks and applications to collect different types of data separately. Moreover, the same data can hardly be shared and reused among different applications, resulting in a duplication of data collection and a waste of resources. So there is a great significance to construct a large scale and universal REM, which can integrate data sources of radio environment and avoid the cost of the re-constructing databases. Concerned with the problems stated above, we propose to leverage Mobile Crowd Sensing (MCS) for REM data collection. MCS is a novel sensing paradigm that empowers everybody to contribute sensed or generated data from their mobile devices, aggregates and combines the data in the cloud for crowd intelligence extraction and people-centric service delivery [2]. Compared with the traditional data collecting technologies, MCS collects the environment information by built-in sensing modules in the mobile terminals, thus has the properties of mobility, node ubiquity, powerful storing and computing abilities. Presently, MCS has been widely used in many applications including measuring pollution [2], analyzing social behaviors [3-4] and detecting traffic condition [5]. Such application cases have proved that MCS is an excellent solution for large scale, high dimension data collection. With the advantages of low cost of network deployment, better system scalability and the mobility of the terminals, MCS could be an excellent scheme for REM data collection, which is the motivation of our work.

This paper is about the details of designing the REM construction architecture based on MCS. Our design has several novel contributions to deal with large scale and high dimension data collection. Our key contributions are as follows:

- We design a novel REM construction architecture based on MCS, where the ubiquitous, massive and high dimension REM-related data can be sensed by the terminals carried by mobile users.
- We discuss some design issues related to the life cycle of the MCS for REM data collection including REM task creation, REM task assignment, individual task execution and REM data integration. In these issues, we also describe our mobile sensing Android based applications. We also define the collected data types and some REM data parameters.

The rest of the paper is organized as follows: Section Ⅱ outlines the architecture of the system and the system functions. Section Ⅲ describes our method for several design issues. Section Ⅳ shows some results of our system and section Ⅴ is the conclusion.

2. Related works

In the related studies, REM has been widely applied to interference management and users' coexistence in various wireless networks (WLAN (802.11), WiMAX (802.16), WRAN (802.22)) [6], radio resource management in 3G [7], high-speed trains LTE management [8], dynamic spectrum access and sensing [9-10], network integration and collaborative communications [11], and localization [12].

The primary problem to build a REM is how to collect a large amount of data. Firstly, the radio signal is ubiquitous, so it is very difficult for the sensors to cover the targeted radio environment [13]. The higher accuracy of the REM, the more sensor nodes are needed to be deployed. Moreover, more than a dozen of data types are required to build a universal REM and each type has more than one attribute. Therefore, a general sensor node can hardly complete this complex data collecting task.

The current data collection methods for REM can mainly be categorized into three types: (1) integrating or accessing the related information directly from existing databases; (2) estimating radio propagation characteristics by software tools; (3) leveraging cognitive radios devices or networks to sense data. We will discuss these methods in details.

First, gathering data from the existing database is a relatively convenient way, while the data updating time depends on the updating period of the underlying database. Moreover, the historical information is not stored in the underlying database. Riihijärvi uses external datasets to build REM, but the update cycle of the external datasets is very long, which makes datasets unable to meet the real-time requirement of REM [14]. Constructing REM in this way is difficult to satisfy the upper-layer applications with the requirement for real-time and historical information.

Second, the way to characterize and estimate the properties of radio transmission based on software is to calculate the signal attenuation by modeling so that we can better plan the radio environment [15-16]. The model in [17] clearly gives a solution to the signal diffraction problem caused by the occlusion, but this requires an accurate vector model of all three-dimensional structures, with limited data and resolution in most experimental environments, it cannot be applied to applications that require high accuracy. The above-mentioned estimation method usually provides limited data, bad accuracy of the data.

Third, the method based on wireless device or external network mainly uses the information sensing ability of heterogeneous spectrum sensor network to collect data [18-19]. According to network structures, the wireless sensor network can be divided into the direct-connect wireless sensor network, multi-hop wireless sensor network, cluster-based wireless sensor network and wireless sensor network based on mobile sensors [20]. The direct-connect wireless sensor network has a simple structure and a small coverage area, which is suitable for small-scale applications. The multi-hop wireless sensor network and Ad-Hoc networks can support large network scale than the direct-connect network, but it is still not suitable for large scale network because of the bandwidth bottlenecks and "hot spots" around the sink nodes and congestion problems [16,21]. In the wireless sensor networks based on mobile nodes, mobile nodes move in the network according to certain rules, and the nodes in the mobile process will simultaneously transmit the data. The key of wireless sensor networks based on mobile nodes is how to achieve a specific optimization goal by controlling the movement of the mobile nodes.

3. System architecture

3.1 The REM Based on MCS Architecture

Figure1 shows the overview of our system based on MCS. From bottom to upper layer, the system includes data sensing layer, data collection layer, data processing layer, data analysis layer and visualization layer. In the data sensing layer, a large number of mobile terminals constitute the mobile crowd sensing network, and they play the role of data sensing by running our data collecting APP named wireless detect. The mobile terminals upload the sensing data to our cloud servers via Wi-Fi/3G/4G networks. The data collection layer is mainly responsible for receiving data, sensing node selection, task allocation, making incentive mechanism to recruit enough interested nodes to participate into the sensing tasks. The data preprocessing like arranging the data format, data fusion, etc. The data analysis layer is responsible for the statistical analysis and calculation of the radio environment relevant parameters. At last, the visualization layer shows the REM relating results in the forms of the field strength map, heat map, and some other maps.

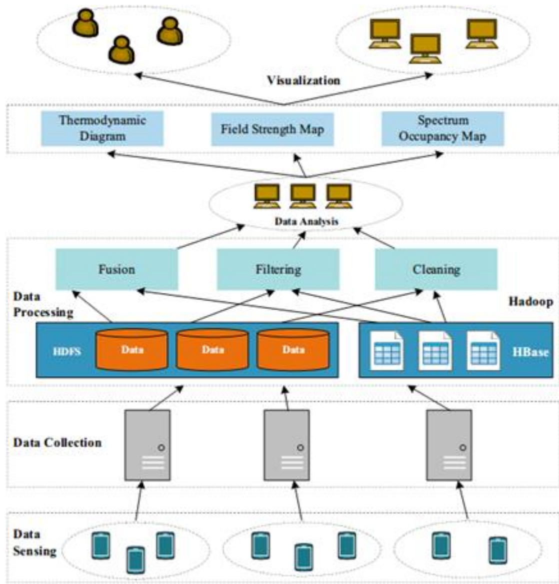

Figure 1. Systems network architecture

3.2 System Function

Our design involves various functional blocks, communicating via well-specified interfaces. To establish a complete radio environment map, the fundamental problem is the collection of a large number of data with complex types and data processing and visualization. Our system consists of five different function modules, data sensing, data collection, data processing, data analysis and visualization, each of them has its own function. In this section, we provide the main components of our system architecture, their functionality and interactions.

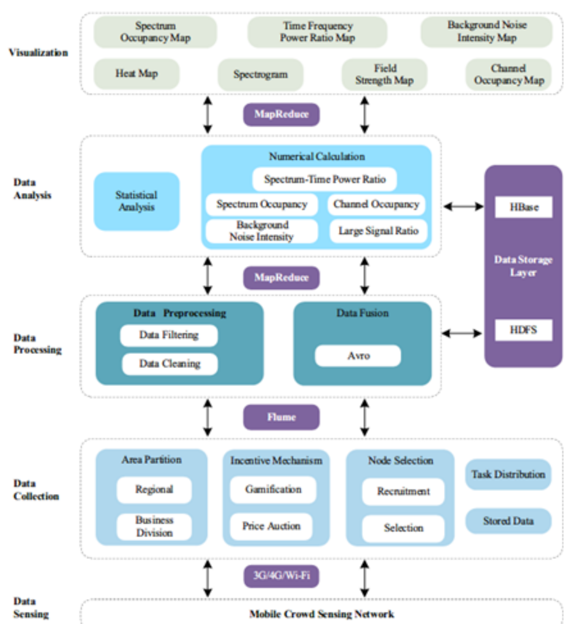

Figure 2. System functional architecture

3.2.1 Data Sensing Module

The data sensing function is operated by the MCS network, which is organized by mobile terminals carried by mobile users. When a mobile user receives a data sensing task, it will determine whether or not to involve in the task. If so, it will collect the required data by the sensing module embedded in the terminal. Moreover, it will also upload the data to the web server by different types of network accessing technologies like Wi-Fi/3G/4G. In our system, the perception of user-uploaded data and call the mobile phone Baidu API real-time construction of heat map and signal strength map. Users can use wireless detect real-time view of the environment in which the use of radio spectrum resources.

3.2.2 Data Collection Module

This module mainly includes area partition, incentive mechanism, nodes selection, task distribution, data storage, data distribution, etc. The area partition is designed to identify whether a sensing task refers to a geographical location or is based on some social relationships. In our system, we divided it into regional division and business division. The incentive mechanism is used to reduce the cost of the platform as well as attracting enough sensing users. Furthermore, node selection mechanism needs to select some appropriate nodes for the data sensing, and also needs to assign the sensing nodes to the corresponding sensing tasks if there is more than one task.

3.2.3 Data Processing Module

It mainly includes two functions: data preprocessing (filtering and cleaning) and data fusion, which is implemented by the MapReduce workflow. The data processing flow is as follows. Firstly, the Avro in the data fusion module compresses various types of formats of the data and merges massive small files into large files to improve the efficiency of MapReduce. Secondly, as the raw data is varying in data types, the data cleaning and filtering can play an important role to remove the noise and interference such as error data. Thirdly, these data are processed by our Hadoop cluster, and the processing results are stored in HDFS.

3.2.4 Data Analysis Module

It is responsible for the statistical analysis and calculation after the data pre-proceeding. In order to exhibit the radio environment on the map, it needs to analyze and calculate the data to get related parameters such as the channel occupation, frequency band occupancy, background noise intensity, large signal ratio, etc. In this module, the systems MapReduce program call for the pre-processed data from HDFS and send the computing results to HBase for the ultimate visualization.

3.2.5 Data Visualization Module

The Visualization module is responsible for the REM-related data parameters exhibition. We designed the visualization for the REM properties. The system can show the Wi-Fi signal coverage, cellular signal coverage heat map, Wi-Fi channel occupation ratio map. The visual REM makes it easy to identify the radio environment of the target area. The REM can provide different parameter maps as shown in part 5.

4. Design issues

In [17], the author proposed 4W1H model in mobile sensing and divided the MCS life cycle into four phases: task creation, task assignment, individual task execution, and crowd data integration. Based on this, we will discuss the following key design issues, REM task creation, REM task assignment, participants recruiting and participants' selection.

4.1 REM Task Creation

The task creation is to specify the sensing time and coverage area for the REM. In our system, the web server releases the sensing tasks in our website. REM is to support long spatio-temporal information for the upper layer applications, so the sensing time is continuous.

4.2 REM Task Assignment

In this stage, our system is responsible for recruiting and selecting participants for the MCS Task. Correspondingly, this stage includes participants recruiting, participants' selection and incentive mechanism.

4.2.1 The Participants Recruiting

The main goal of participants recruiting is to encourage enough people joining the sensing task and get more radio environment data. The system will publish a sensing task notice in the website and then push the notice to the APP installed in the users' mobile phones. These participants are seeds. In order to inform as many as volunteers, these initial participants will send the sensing task to other people, like nearby users or friends based on social relationships.

We have designed a short-range task spreading mechanism to recruit more participants based on Wi-Fi Direct communication technology. As is shown in Figure 3, the MCS network constructed by participants who carried mobile phones is divided into clusters based on the properties of a sensing task. Each cluster has a cluster header and other nodes. The nodes of the clusters need to complete the sensing task according to the rules of a sensing task and upload the sensing data to the data server of the MCS platform by TCP/IP connection. The head of the cluster is responsible for receiving the sensing tasks from the MCS platform, sending to nearby users and recruiting more participants joining the sensing task. When the cluster heads need to recruit more users, they will scan nearby users and send the sensing tasks to the users by Wi-Fi Direct. If a user is interested in the sensing tasks, they will negotiate with cluster headers and join the sensing task. When the new participants join in a cluster, the cluster header will send more information about the sensing task, the way to download the sensing APP and upload the sensing data.

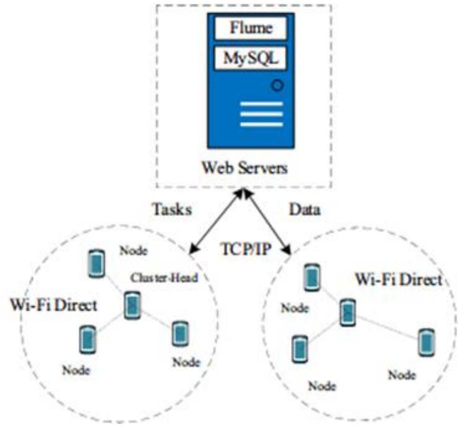

Figure 3. Short-range task spreading mechanism based on Wi-Fi-Direct

4.2.2 The Participants Selection

The participants' selection step needs to select the appropriate users to join in the sensing process. It contains how to assign users to the correspondent sensing tasks subjected to some constraints: reducing the whole cost, minimum sensing delay, etc. In our system, we select the nodes based on the trade-off between cost and the balancing of node participation.

Sometimes, the sensing capacity of a user's terminal is relatively weak to finish the high dimension data sensing. They can only operate part types of the data that needed by the REM. Therefore, we propose to divide the high-dimensional data sensing task into several sub-tasks. Then, massive nodes with different sensing capacities may complete the whole task cooperatively. As shown in Figure 4, in order to finish the sensing task with higher data dimension (m dimensions), we have to divide the m dimensions sensing task into k sub-tasks. Consequently, with each node sensing parts of the data, the whole m dimensions' data collection task could be finished. Here, the participant's selection problems can be abstracted to divide multiple nodes into corresponding sub-tasks. In order to assign each node to an appropriate subtask, such as reducing the whole sensing cost or making nodes participating sub-tasks evenly, we present to make a trade-off between the whole sensing cost of the platform and the equality of node participation.

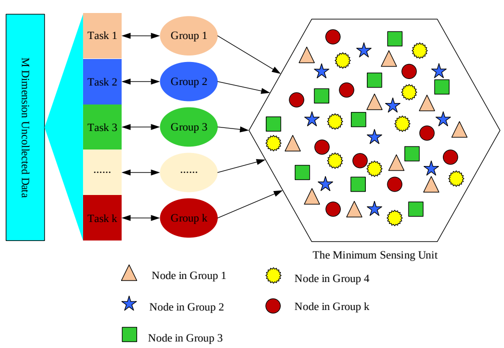

Figure 4. k groups cooperatively complete the m dimensions' data sensing

4.2.3 Incentive Mechanism

In order to encourage enough users to join in the sensing period, the platform needs to leverage some incentive mechanisms. In our system, volunteers send their confirmations back to the platform with their price for the task. The platform receives the confirmation, and in node selection phase, the platform pays rewards in forms of money or other ways to the volunteers for the data sensing. The incentive mechanisms used in our project are monetary reward incentive. Based on the node selection stage, the platform and users negotiate the sensing price. In order to reduce the cost of the whole sensing cost, the platform is prone to choose the lowest quotations and make users distributed to different sub-sensing tasks evenly.

4.3 Individual Task Execution

In this stage, participants conduct sensing tasks and upload the sensed data to the MCS platform. The participants receive the sensing tasks and then collect the radio environment data. There are enough participants distributed in the target places collecting data. After radio environment data collection, the participants upload the data to the MCS platform server. The design issues in this stage are MCS module design, data acquisition frequency, data collect types and data upload.

4.3.1 Mobile Crowd Sensing Module Design

The sensing module is mainly composed of functions like data collection, data communication , control, data storage and interface structure. As illustrated in Figure 5, we develop the data sensing APP by Android SDK (Software Development Kit). for data collection, the API of the android system is called to make the sensing module to collect data. In data communication module, we develop a method of File_upload (), uploading the data files to servers by HTTP protocol. We also using the HTTP protocol to receive data from the server to build the heat map and signal strength map of the radio environment information. During the process of file upload, the raw data would be encapsulated, error handled and parsed. In the control module, a control class is used to manage all other modules. In data store module, the method of write_sensor_info() in service writes data into SD card by Java data stream. In Interface module, we create an interface based on UI (User Interference) and set all buttons in the layout. The heat map and signal strength map is passed though the interface to show the environment where the user perceives the radio spectrum resource usage.

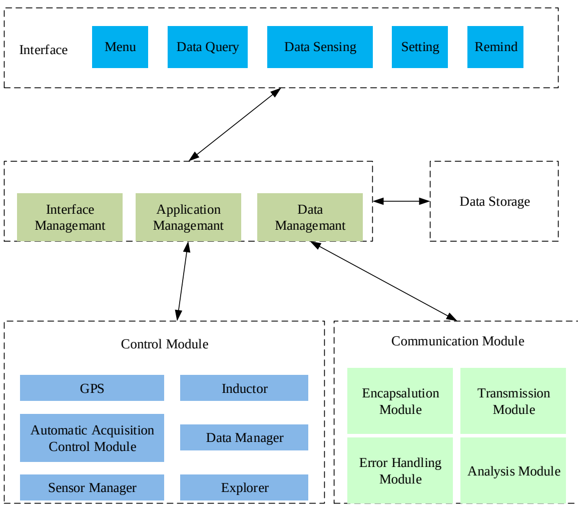

Figure 5. The sensing architecture in a mobile terminal

Concerning the ANN, the main input features are depths and RD values of neighboring CUs as well as a MergeFlag binary feature. The results reported list a complexity reduction of 47.5% for a BD-Rate increase of 1.17%. However, these results do not consider the extra computation involved in the retraining of the ANN by the secondary threads, which in all likelihood contribute a non-negligible amount of complexity to the overall encoding procedure.

4.3.2 Data Acquisition Frequency

The user consumes the power of the mobile terminal and network traffic (even the time cost of the user) during the radio environmental information collection process. If the data acquisition frequency is too tight, it will cause data redundancy. And if too sparse, it will cause data integrity problems. Therefore, in the system, to infer the user's current environment through the users' history data, and the data acquisition frequency is adjusted automatically according to the user's current environment information. In order to optimize a user's mobile terminal resources and improve the quality of data, the system divides users' current environment into three kinds of scenes: indoor, outdoor, and in car. The scene is judged as follows.

Table 1. Sense frequency

Types	Sense Frequency	Judgments based
Indoor	Low	SSID: Repeat with the SSID in the history data; Wi-Fi hotpots: The total number of Wi-Fi hotpots scanned is almost constant; Speed: Less than 1.5m/s.
Outdoor	Medium	SSID: Repeat with the SSID in the history data; Wi-Fi hotpots: The total number of Wi-Fi hotpots changes; Speed: 1.5~5m/s
Driving	High	SSID: The SSID repetition rate in historical perceptual data is low. Wi-Fi hotpots: The total number of Wi-Fi hotpots changes; Speed: higher than 5m/s

4.3.3 Data Collection Types

These types include the basic data types such as, Wi-Fi network data and cellular network data, etc. The REM-related parameters like Wi-Fi and cellular network data are shown in Table Ⅱ and Table Ⅲ respectively. As shown in Table Ⅱ, Wi-Fi network data is divided into Wi-Fi connection data and Wi-Fi scanning data. The Wi-Fi connection data refers to the information of the Access Point (AP) connected to a sensing node, and Wi-Fi scanning data refers to the information of all the APs scanned by the sensing node. Table Ⅲ shows the cellular network data, such as information of GSM, CDMA, LTE, etc.

Table 2. Wi-Fi network data

Data Types	Parameters	Parameter Specification
Wi-Fi Connection	Network_ID	Network identification
	Link_SSID	Service Set Identifier of Link
	Link_BSSID	Basic Service Set Identifier
	Supplicant State	Connection status of the AP (connecting/completing)
	RSSI	Received Signal Strength Indication.
	Link Speed	Link Speed
	IP	Internet Protocol of Mobile phone.
Wi-Fi Scanning	Frequency	The primary frequency of the channel.
	Level	Signal strength
	Capabilities	EncryMode
	Scan_SSID	Service Set Identifier of Scanning.
	Scan_BSSID.	Basic Service Set Identifier of Scanning

Table 3. Cellular network data

Data Types	Parameters	Parameter Specification
GSM	Type	Network Type
	CID	Cell Identity
	LAC	Location area code
	RSSI	Received Signal Strength Indication
	BER	Bit Error Rate
	Valid Cellular	The number of the adjacent base stations.
	PSC	The primary scramble code of adjacent base stations.
CDMA	CDMA_RSSI	CDMA Signal Strength
LTE	LTE_RSSI	LTE Signal Strength

4.3.4 Data Uploading

As shown in Figure 2, the terminals connect to the network through 3G/4G/Wi-Fi and other ways, and they establish TCP/IP connections to the Web server so that the data is transmitted to the Web server by exploiting HTTP protocol. The Flume component installed in the Web server is used to monitor file update. If there is a file updating event, the Web server will automatically upload the new data to the data center built by the Hadoop cluster.

As shown in Figure 3, the participants will upload the sensed data to the MCS platform server. First the users will connect the server by establishing TCP/IP connections. Then the participants will transfer the radio environment data to the server and put the data in database for further processing

4.4 Crowd Data Integration

In general, the main issue of the MCS platform that is to process, analyze the raw data received from mobile terminals, and visualize the required results eventually. Correspondingly, the crowd data integration mainly includes data processing and data analysis.

4.4.1 Data Processing

We leverage the Flume software to automatically upload the new sensing data from Web server to big data processing platform which is composed of the Hadoop cluster. The small files are sequenced and then constituted into large files by the Avro plugin, which can improve the efficiency of the subsequent steps such as data filtering, data cleaning, data processing, and analysis. Here, the Avro compression and small-files-tuning methods are used to improve the efficiency of MapReduce. Finally, the MapReduce programs are developed to remove the redundant sensing data.

4.4.2 Data Analysis

Data analysis module is responsible for the statistical analysis and the calculation of radio environment. As shown in Table Ⅳ, the relevant parameters, according to the requirements of the upper arm need to be computed. Later, all of the analysis results are stored in HBase for data visualization.

Table 4. Numerical index

Numerical Index	Formula	Parameter Definition
Channel Occupancy	$\rho = \frac{T_1}{T} \times 100\% = \frac{c}{n} \times 100\%$	T_1, duration of the signal exceeds the receiver threshold level. T, measurement time. n, scanning times per channel. c, occupancy times.
Band Occupancy	$\theta = \frac{m_1}{m} \times 100\%$	m_1, the number of channels whose level is bigger than the threshold level in the frequency band. m, denotes the total number of channels measured.
Background Noise Strength	$B_n = \frac{\sum(rb_n - rb_0)/(40 - rb_0)}{FS_n}$	rb_n, value of noise strength. rb_0, sensitivity test system.FS_n, total number of channels.
Large-signal Ratio	$S_s = \left(\frac{E_{max}}{90}\right)^3 \times \sqrt[3]{\frac{SS_n}{FS_n}}$	E_{max}, maximum signal field strength, the strength which more than 50% of the average strength.FS_n total number of channels.
Time Band Power Ratio	$P_t = 1 - \frac{15 \times t \times FS_n}{\iint E_f}$	t, channel measured time.E_f, measured field strength value

4.4.3 Visualization

Our REM visualization is based on Baidu Map, by calling the Baidu Map API, radio environment map is built based on the analysis results stored in MySQL. Where the MySQL is in the Web server, and the data in MySQL is automatically imported via Sqoop from HBase.

5. Results

We designed and implemented prototype REM system based on MCS, then collected the radio environment data of Chongqing University of Posts and Telecommunications (CQUPT). The collected data was uploaded to our system and analyzed, several heat-maps and figures are as follows.

Figure 6 shows a prototype heat map which provides the overall of Wi-Fi signal strength in CQUPT sensed by mobile terminals. Good signal strength occupied zones appeared as islands of red or yellow in otherwise green or blue settings. The initial visualization made it easy to identity good signal strength areas, as is shown Block A and Block B. As we can see a high occupancy of Wi-Fi is shown in the map, while only a few areas of the school have good signal strength as Block A.

Figure 6. The heat map of Wi-Fi signal strength

Figure 7. The heat map of user density

Figure 7 shows a prototype heat map for user density, which is constructed by the user geographic information. The relatively high user density areas are in red or orange as Block A/B/C, while the relatively low user density areas are in blue or green. As is shown in the figure, the distribution of the user density in the school area is not uniform. However, the results are as expected. The high user density areas are teaching area and living area, so most of the students and staffs are studying or working in these areas which are occupied by red or orange.

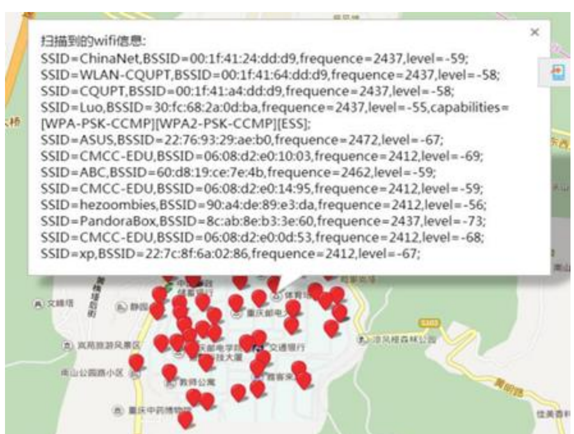

Figure 8. The information of Wi-Fi connected and scanned

As is shown in Figure 8, lots of Wi-Fi properties can be seen on the banner. The properties collected by participants are as SSID, BSSID, frequency and the Wi-Fi signal strength level. This information belongs to the Wi-Fi signal sources sensed by the nearby participants. The density of the red nodes represents the density of the Wi-Fi signal sources. As we can see in Figure8, the density of the Wi-Fi signal source is not uniform. This result is expected. The large density areas have more classroom and offices, which requires more Wi-Fi sources are. The small density areas are outdoor playgrounds, that's why less W-Fi are needed.

Figure 9. The distribution of LTE signal strength

Figure 9 is a heat map of LTE shows the coverage of LTE and signal strength in the school. The color gradient of the shades can be seen in the map. The pink shades indicate the bad LTE signal which is less than -90dbm, while the dark red shows better LTE signal which is more than -40dbm and the red gradients denotes the signal strength between -90dbm and -40dbm. As we can see in the picture, there is still lots places can't be covered by LTE signals. This result can be used to help the ISPs to build more LTE base stations until the school is all covered by the LTE network.

Figure 10. The distribution of LTE signal strength around the subscriber

Figure 10 shows the LTE signal strength map within 5 km where the user is located, which provides a new solution for radio network optimization. The different colors represent different signal strength. As we can see in Figure 10, most of the signal nodes are orange, which represents that the LTE signal strength of these places are between -60-70dBm. Some signal nodes are pink, which represents that the LTE signal strength of these places are between -90-100dBm. These places need a better solution to optimize the LTE network.

6. Conclusion

In this paper, we introduced MCS to collect data for REM construction. We believe this is an important design point to deal with the large-scale distributed, high dimension and massive data sensing tasks. We designed five layers reference architecture for REM. We also considered some design issues based on MCS life cycle: REM task creation, REM task assignment, individual task execution and crowd data integration. Based on our analysis, MCS has several advantages over other traditional data collecting methods in constructing the REM. In the future, we plan to design more effective incentive mechanisms for participants recruiting, MCS networking, and collaborative data collecting, etc.

Acknowledgement

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