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Enhanced Fingerprinting and Trajectory Prediction for IoT Localization in Smart Buildings

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Abstract: Internet of Things (IOT) is the primary services in smart automated systems. Markov chain prediction model to assist positioning called Novel Localization Method (LNM).The Neighbor Relative Received Signal Strength (NRSS) used to build the fingerprint database and adopts a Markov chain prediction model to assist positioning as Novel Localization Method (LNM).The history data of the pedestrian's locations are analyzed to positioning for various devices. Performance evaluation conducted in realistic environment demonstrates localization performance compared with existing schemes, when the problems of device heterogeneity and WiFi signals fluctuation exist future.

Keywords: Mobile Internet of Things (IOT), Novel Localization Method (LNM), Location Base Services (LBS), Current Neighbor Difference (CND), Received Signal Strength (RSS).

I. INTRODUCTION

It is inter-networking of physical devices, vehicles (referred "connected devices" and "smart devices"), buildings and other items embedded with electronics, software, sensors, actuators and network connectivity enable these objects to collect and exchange data. Opening tremendous opportunities for novel applications that improves the quality of our lives. According Location services use device or human location sense by mean of devices like GPS, Wi-Fi, and Bluetooth to provide simplicity in daily activity and personalize offering and services to users. With the development of IOT, LBS has become increasingly important and extensively used. A Passive method: In it, the tracked person does not carry any electronic device and actively participate in the positioning process. Active method: In it, tracked person carries a physical electronic device, which can collect and process some information and send the results to a localization server for further processing. Any structure that uses automated processes to automatically control the building's operations including visitor management, personal assistance, heating, ventilation, air conditioning, lighting, security and other system. It is an intelligent building "one which provides a productive and cost-effective environment through optimization of four basic elements: structure, systems, services and management, and the interrelationship between.

Industry, Infrastructure, IoT, M2M. industrial buildings are becoming smarter. They currently embody a growing style of technologies that are part of the internet of Things (IoT) phenomena. Across the world, new buildings are being made with each wired and wireless IoT infrastructure that allows innovation.net| the web|internet} of Things refers to the ever-growing network of physical objects that feature associate degree information processing address for internet property, and also the communication that happens between these objects and alternative Internet-enabled devices and systems. The Internet of Things (IoT), referred because the web of Everything (IoE), consists of all the web-enabled devices that collect, send and act on knowledge they acquire from their close environments mistreatment embedded sensors, processors and communication hardware. meaning Consumer devices embody sensible TVs, sensible speakers,toys,wearablesand sensible appliances. sensiblemeters, industrial security systems and sensible town technologies like those accustomed monitor traffic and weather are examples of industrial and enterprise IoT devices.

The a lot of information that IoT devices collect, the smarter they'll become. Cities can rework into good cities through the utilization of IoT connected devices. Smart homes, thermostats, lighting systems and coffee makers will all collect data on your habits and patterns of usage. The IoT device will be connected to an IP network to the global Internet. Commercial IoT, where local communication is either Bluetooth or Ethernet (wired or wireless). The IoT device will typically communicate only with local devices connected. On a broader scale, the IoT can be applied to things like transportation networks: "smart cities" which can help us reduce waste and improve efficiency for things such as energy use serving to United States of America perceive and improve however we tend to work and live.

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IoT permits for just about endless opportunities and connections to require place, many of which we can't even think of or fully understand the impact of today. It's not hard to see how and why the IoT is such a hot topic today; it certainly opens the door to a lot of opportunities but also to many challenges. For example you're on your thanks to a meeting; your automotive might have access to your calendar and already recognize the simplest route to require. If the traffic is significant your automotive would possibly send a text to the opposite party notifying them that you simply are going to be late. What if your timer wakes up you at via.mail. and then notifies your kitchen appliance to start out production occasional for you? What if your workplace instrumentality knew once it had been running low on provides and mechanically re-ordered more? What if the wearable device you utilized in the geographical point might tell you once and wherever you were most active and productive and shared that data with alternative devices that you used while working?

II. RELATED WORK

Andrew Mackey ,Petros Spachos, "Performance evaluation of beacons for indoor localization in smart buildings". The concept of Internet of Things, indoor location services using Bluetooth Low Energy beacons has become a growing reality. Many systems uses Received Signal Strength Indicator based location methods. The unpredictable propagation of these signals, in combination with surrounding signal noise and variable environmental conditions, makes it difficult to implement such systems as a simple entity. This paper compares three popular beacons, presents a simple mobile application based Kalman filter, and explores the correlation between transmit power and desired Kalman filter parameters.

Jeffrey D. Poston, Javier Schloemann, R. Michael Buehrer , V. V. N. Sriram Malladi, Americo G. Woolard, " Towards indoor localization of pedestrians via smart building vibration sensing"
In this paper authors check the feasibility of collecting vibration sensor readings within a building to locate pedestrians by their footsteps. Vibration propagation in buildings is different than radio wave propagation in free space, thus prompting one to question the suitability of conventional positioning algorithms for this task. authors presents the results of experiments conducted with actual measurements from an instrumented, smart building. Authors expect such buildings to become more prevalent in the future thanks to the technical advances and cost reductions provided by the Internet-of-Things (IoT). The promising initial findings indicate that time-difference-of-arrival, within a limited spatial extent, could be a viable localization technique, and these results encourage further research into vibration-based indoor localization.

Qichuan Yang, Zhiqiang He, Kai Zhao, Tian Gao, "A Time Localization system in Smart Home Using Hierarchical Structure and Dynamic Frequency"
A time localization system (TLS) based on off-the-shelf smartphones with WiFi identification. TLS can identify the received signal strength indication (RSSI) of home and construct radio map of users' time route without site survey. As designed to service the smart devices in home, TLS applies the time interval as the distance of positions and as the variables of WiFi environment to mark time points. TLS service system for timeline localization achieves a median accuracy of 70 seconds and is more robust compared with nearest neighbor localization approach.

M. Victoria Moreno , Antonio F. Skarmeta," An indoor localization system based on 3D magnetic fingerprints for smart buildings"
Human behavior modeling and activity interpretation is increasing interest in the Information Society.Internet of Things technologies enhance the situational awareness or "smartness" of service providers and consumers alike. User-centric sensing systems are ideal candidates for ubiquitous observation purposes thanks to the indispensable role of mobile phones in everyday life. This paper presents a novel approach for mobile phone centric observation applied to indoor localization for smart buildings and provide accurate localization data used for offering customized IoT-based services in buildings.

Xinyao Tang ,Ming-Chun Huang, Soumyajit Mandal, " An "Internet of Ears" for crowd-aware smart buildings based on sparse sensor networks"
This paper uses sparse low-power sensor networks which uses passive seismic sensors for crowd-aware smart buildings, named "Internet of Ears (IoE)" which detect human footsteps, estimate walk direction, and track person position. An energy-based thresholding footstep detector was developed using wavelet transform for pre-filtering the noise-prone ambient vibrations detected by the sensors.Indoor occupant localization based on a least squares (LS) method and using improved time delay estimation is introduced. Experimental results in two different buildings show the effectiveness of the footstep detection and occupant localization methods, with detection accuracy of 98.3% and average localization error < 25 cm.

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III. METHODOLOGY

With rapid development of IoT technology various applications like IoT base smart home, parking and smart campus came to existence. Location service is one of the primary services in smart automated systems of Internet of Things (IoT). For various location-based services, accurate localization has become a key issue. Recently, IoT localization systems for smart buildings has been attracting increasing attention. It is expected that popularization of smart building technology will redefine the way we work and live in the future. Wireless localization has become very important in the IoT context and a variety of solutions have been proposed like smart campus etc. RSS fingerprint is more practical and widely applied, since the IEEE 802.11 APs are pervasively deployed nowadays. The fingerprint-based localization techniques are considered more attractive because of their advantages of low deployment cost and robustness in environment with interferences.

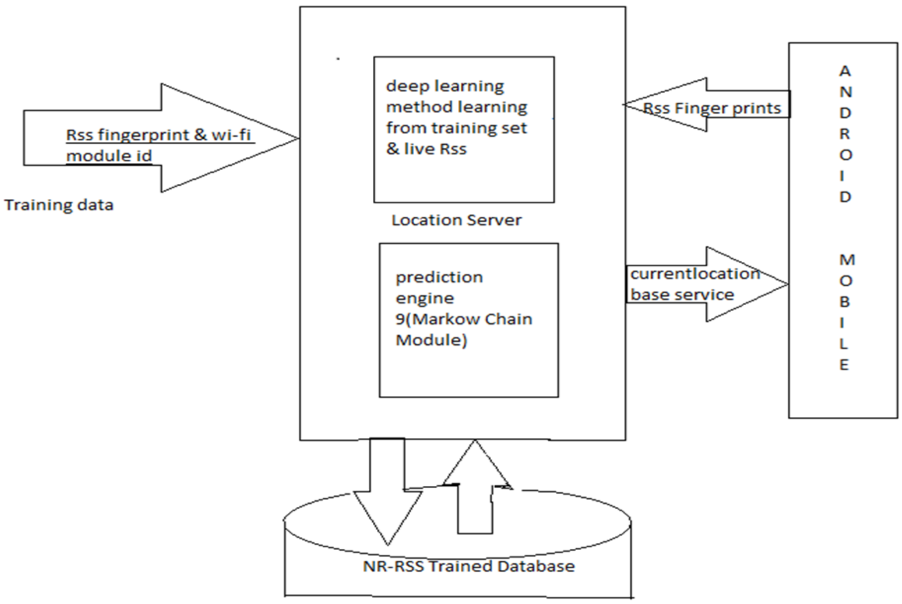

Figure 2.3 Architecture Of System

We have proposed localization base on location-fingerprinting-based systems which is based on mathematical model. The main challenge is the fact that the techniques are vulnerable to environmental dynamics and heterogeneous devices. Our proposed system work in two phases offline and online phase. In offline phase the fingerprint that is received single strength value maps of interest region are built using empirical measurement operations or a signal propagation model. In online phase the mobile devices measure the RSS at an unknown position. Then, the measured RSS is matched with the fingerprint radio map in the database, and the best matching position information is identified.

In the proposed system, we have set some calibration points for offline training with respective to set AP's in the building. We the help of surveying we have calculate RSS and NR-RSS value for each calibration point. Fingerprint-based localization systems must scan the surrounding RSS on each positioning at online localization phase. It is a high-energy-consuming operation for smart objects such as smartphones. It is more efficient to predict the object's movement by means of mathematical models. Thus, we apply the Markov-chain model to conduct object's trajectory analysis, which can reduce the energy consumption. In the Markov-chain model, localization object is likely to be moving objects equipped with mobile devices (such as robots and vehicles) in IoT. From the point of purposiveness, their movements have a certain probability (degree of purposiveness), complying with the principle of a Markov chain. In addition, the probability of object's movement can be obtained through the process of collecting and training.

Fingerprint Trajectory

In the Markov-chain model, each object's movement is modeled as a Markov process, and the probability of each movement only depends on the object's current position. The building map is modeled as a cellular structure and is equally divided into hexagonal cells. The object is located at a cell, represented as v0 at time 0, . At time 1, it will either stay where it is or move to one of the six neighbors, v1, v2, v3, v4, v5, and v6.At time 2, it will also stand or move to one of the current location's six neighbors. This procedure is then iterated at times 3, 4, . . . ,t. The first number in parenthesis is the sequence number and the second is the orientation index, namely, the object's movement state. The process continues until enough history data are collected at time i.

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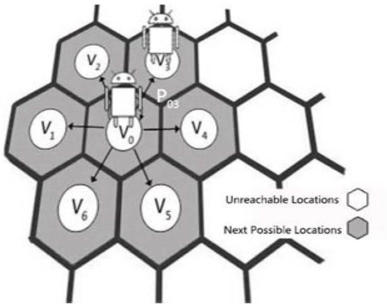

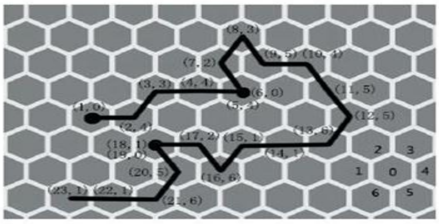

Random pedestrian's trajectory.

The MPM is built to predict the object's following movement state.

$$Pi=\begin{pmatrix} 0 & 0 & 0.33 & 0 & 0.33 & 0.33 & 0 \\ 0.25 & 0.50 & 0 & 0 & 0 & 0 & 0.25 \\ 0 & 0.50 & 0 & 0.50 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.50 & 0.50 & 0 \\ 0.25 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.50 \\ 0 & 0.67 & 0.33 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Prediction:

$(\mu_1^{(k+1)}\ \mu_2^{(k+1)} \ldots \mu_n^{(k+1)})$

$$= (\mu_1^{(k)} \mu_2^{(k)} \ldots \mu_n^{(k)}) \cdot \begin{pmatrix} p11 & \cdots & 1n \\ \vdots & \ddots & \vdots \\ pn1 & \cdots & pnn \end{pmatrix}$$

namely

$\mu^{(k+1)} = \mu^{(k)} \cdot P$

The object's next motion state probability vector can be calculated

$$\mu^{(i+1)} = \mu^{(i)}\ P(i)$$

= (0,1,0,0,0,0,0)

$$Pi=\begin{pmatrix} 0 & 0 & 0.33 & 0 & 0.33 & 0.33 & 0 \\ 0.25 & 0.50 & 0 & 0 & 0 & 0 & 0.25 \\ 0 & 0.50 & 0 & 0.50 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.50 & 0.50 & 0 \\ 0.25 & 0 & 0 & 0.25 & 0.25 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0.25 & 0.25 & 0.50 \\ 0 & 0.67 & 0.33 & 0 & 0 & 0 & 0 \end{pmatrix}$$

= (0.25,0.50,0,0,0,0,0.25)

Thus, according to the prediction analysis, the object most likely directly moves left next time because the 1st index has the highest probability 50%. The localization process runs as follows: the mobile devices can scan the WiFi signals and periodically send information to the localization server. The server combines the received RSS with the history neighbor RSS information to obtain the NR-RSS; then the NR-RSS is compared with all entry locations in the NR-RSS fingerprint database and the most matching one is determined to finish the location estimation. With the mobile device moving, the trajectory of its movement is constantly recorded. When the historical data reach a certain amount, location estimation is mainly performed by the MPM. That is to say, during this phase, location estimation is mainly based on the MPM and supplemented by NR-RSS matching.

NR-RSS Matching Localization: After initializing, system will localize mobile devices by our novel NR-RSS match solution. First, the accelerometer sensor in the smart device is utilized to judge whether the mobile device is in motion or stands. If the mobile device still stands, its current location is the same as the last localization outcome. Otherwise, when the mobile device moves to the next place, it sends the raw ambient RSS values to the fingerprint server. When history

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data are accumulated to a certain amount, the prediction model is built. For the processing and matching stage, the first step is to calculate the RSS difference value of the current location and its last adjacent location (LAL). This difference value is called current neighbor difference RSS (CND-RSS). LAL has the corresponding NR-RSS stored in the NR-RSS fingerprint map. Therefore, the next thing to do is to determine which neighbor of LAL the mobile device arrives at. A metric and a search methodology are used to compare the neighbors, obtaining the best matching one.

Markov-Prediction Localization: Markov-prediction localization from causing the accumulated error, the NR-RSS match localization needs to be executed to verify the accuracy of Markov-prediction localization. When utilizing MPM on mobile devices, prediction result and current NR-RSS are sent to the server, where NR-RSS match localization is conducted to confirm whether prediction result is right. If the localization results estimated by NR-RSS matching and prediction model are nearly the same, server only returns confirming information, implying that the prediction result is valid. However, when they are different, there are two conditions: 1) if the result of NR-RSS matching is located at one of the six neighbors of the last location, the result will be sent to mobile devices as localization result and 2) if the result is located outside the six neighbors of the last location, the PGSL will be run to determine the mobile device position and sent to mobile devices. Moreover, as the prediction model has produced erroneous.

VI. CONCLUSION

As IoT localization systems for smart buildings has been attracting increasing attention. It is expected that popularization of smart building technology will redefine the way we work and live in the future. Location information is basic information in many applications, great efforts have been made by many researchers and different algorithms are proposed. This paper focus on the usability and availability in realistic environment and application systems. It is a good choice to establish a location-based service system for IOT. As compared to traditional algorithm, the proposed scheme is lightweight and briefly and clearly expressed. Thus we have proposed the technique to for localization in smart building using existing infrastructure that is 802.11 widely deployed in almost everywhere. This approach uses relation of neighborhood to calculate the current location of smart object. To overcome high energy task of building frequency map of building, we have proposed markov prediction method. Our techniques provide robust and stable localization accuracy against device heterogeneity and environmental dynamics, which ensures the efficiency of localization.

REFERENCES

[1]. About L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," Comput. Netw., vol. 54, no. 15, pp. 2787–2805, Oct. 2010.
[2]. G. Fortino, A. Guerrieri, and W. Russo, "Agent-oriented smart objects development," in Proc. IEEE 16th Int. Conf. Comput. Supported Cooperat. Work Design (CSCWD),May 2012, pp. 907–912.
[3]. iP. Bellavista, G. Cardone, A. Corradi, and L. Foschini, "Convergence of MANET and WSN in IoT urban scenarios," IEEE Sensors J., vol. 13, no. nj, pp. 3558–3567, Oct. 2013.
[4]. G. Fortino, A. Guerrieri, G. M. P. O'Hare, and A. Ruzzelli, "A flexible building management framework based on wireless sensor and actuator networks," J. Netw. Comput. Appl., vol. 35, no. 6, pp. 1934–1952, Nov. 2012.
[5]. E. Kaplan, C. Hegarty, Eds., Understanding GPS: Principles and Appli-cations. Norwood, MA, USA: Artech House, 2005.
[6]. J.-Y. Lee, C.-H. Yoon, H. Park, and J. So, "Analysis of location estimation algorithms for Wifi fingerprint-based indoor localization," in Proc. 2nd Int. Conf. Softw. Technol., vol. 19, 2013, pp. 89–92
[7]. Fountain C. Koweerawong, K. Wipusitwarakun, and K. Kaemarungsi, "Indoor localization improvement via adaptive RSS fingerprinting data-base," in Proc. Int. Conf. IEEE Inf. Netw. (ICOIN), Jan. 2013, pp. 412–416.
[8]. J. A. G. Martin, A. V. M. Rodríguez, E. D. Zubiete, O. R. Romero, and S. M. Guillén, "Fingerprint indoor position system based," J. Netw., vol. 8, no. 1, pp. 37–44, Jan. 2013.
[9]. Y. Shu, P. Coué, Y. Huang, J. Zhang, P. Cheng, and J. Chen, "G-Loc: Indoor localization leveraging gradient-based fingerprint map," in Proc. IEEE Conf. IEEE Comput. Commun. Workshops (INFOCOM WKSHPS), Apr./May 2014, pp. 129–130.
[10]. C.-W. Lee, T.-N. Lin, S.-H. Fang, and Y.-C. Chou, "A novel clusteringbased approach of indoor location fingerprinting," in Proc. IEEE 24th Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC), Sep. 2013, pp. 3191–3196.
[11]. X. Hu, J. Shang, F. Gu, and Q. Han, "Improving Wi-Fi indoor positioning via AP sets similarity and semi-supervised affinity propagation clustering," Int. J. Distrib. Sensor Netw., vol. 2015, Jan. 2015, Art. no. 109642.
[12]. A. Carroll and G. Heiser, "An analysis of power consumption in a smartphone," in Proc. USENIX Annu. Tech. Conf., 2010,p. 21.
[13]. A. Bose and C. H. Foh, "A practical path loss model for indoor WiFi positioning enhancement," in Proc. 6th Int. Conf. IEEE Inf., Commun. Signal Process., Dec. 2007, pp. 1–5.
[14]. G. Deak, K. Curran, and J. Condell, "A survey of active and passive indoor localisation systems," Comput. Commun., vol. 35, no. 16, pp. 1939–1954, Sep. 2012.
[15]. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system," in Proc. ACM 6th Annu. Int. Conf. Mobile Computer Netw., 2000, pp. 32–43.
[16]. Andrew Mackey, Petros Spachos, "Performance evaluation of beacons for indoor localization in smart buildings"
[17]. Jeffrey D. Poston, Javier Schloemann, R. Michael Buehrer , V. V. N. Sriram Malladi , Americo G. Woolard, " Towards indoor localization of pedestrians via smart building vibration sensing"
[18]. QichuanYang, Zhiqiang He ,Kai Zhao, Tian Gao, " A Time Localization system in Smart Home Using Hierarchical Structure and Dynamic Frequency"
[19]. M. Victoria Moreno , Antonio F. Skarmeta," An indoor localization system based on 3D magnetic fingerprints for smart buildings"
[20]. Xinyao Tang ,Ming-Chun Huang, Soumyajit Mandal, " An "Internet of Ears" for crowd-aware smart buildings based on sparse sensor networks"