A Positioning Algorithm in the Internet of Things

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***Abstract*— Location-based service is one of the vital services in the Internet of Things (IoT) which merge many kinds of technologies, like Zigbee, Internet, Infrared, Bluetooth, 3G, GPRS (General Packet Radio Service), Wi-Fi, etc... Along with rapidly growing IoT, applications from personal electronics to industrial machines and sensors are getting wirelessly connected to the Internet. One of the problems is that these devices usually come with many different hardware solutions. In the art of wireless indoor positioning, a lot of research works have been done, however almost these have not addressed to this presence of hardware heterogeneity yet. This paper proposes a new positioning algorithm which is independent of hardware configurations without offline stage. By using mathematical formulation analysis, we demonstrate its advantages than the other techniques.**

***Keywords*— IoT, wireless technology, wireless indoor localization; fingerprinting; received signal strength.**

I. Introduction

The Internet of Things is a novel paradigm where objects containing sensors, computer, cell phone, or RFID (Radio-frequency identification) tags will be capable to enter the network to communicate with one another and with other devices and services over the Internet to reach common goals [1] [2].

Along with rapidly growing IoT, applications from personal electronics to industrial machines and sensors are getting wirelessly connected to the Internet as in the Figure.1 [3]. When machines communicate directly with other machines, a device collects information by means of a sensor. The sensor then uses a radio transmitter to send the data over a network. The network can be either wired or wireless. Wireless networks can be cellular, satellite, Wi-Fi for wide range communication, or Bluetooth, ZigBee and RFID for short range communication. Once the data arrives at its destination, it can be analyzed and acted upon by either another device or a human being. These data can be environmental data, geographical data, astronomical data, and logistic data. In the various kinds of data, location information in IoT is critical for application in logistics, medical, industrial, public safety, and transport system.

Furthermore, when wireless information access is widely available, it will trigger a high demand for accurate positioning in wireless network, including outdoor and indoor environments [4] [5].

For localization in an outdoor environment, Global Positioning System (GPS) which is released by U.S. Department of Defense works extremely well [6]. Unfortunately, the signal from the GPS satellites is too weak to penetrate most buildings, making GPS useless for indoor localization.

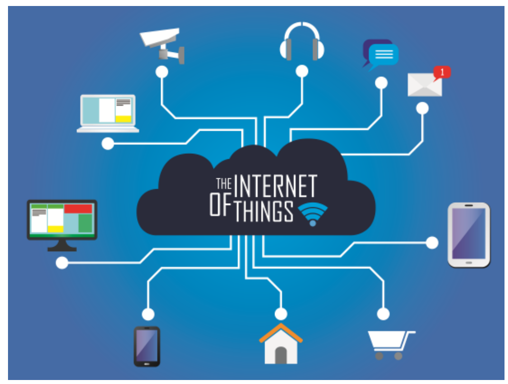

Figure 1. Internet of Things (IoT).

Wireless indoor localization has long been an active research field, and hold promise for many ambient intelligence applications which been designed to provide location information of persons as well as devices and used in many applications such as: medical, industrial, public safety, logistics, and transport system… In wireless indoor localization, fingerprinting-based methods are widely used. This method constructs a fingerprint database and returns user's location based on similar fingerprints. Received signal strength (RSS) is the most common RF signal parameter used as location fingerprints.

In fact, various commercially available hand-held devices and wireless access points (AP) are capable of reporting RSS. In generally, the RSSs are mostly reported in dBm values. One of the problems is that these devices usually come with many different hardware solutions. As a result, reported RSS of these devices (nodes) are different even for the same wireless technology. However, almost RSS based localization schemes did not address to this presence of hardware heterogeneity. As shown in [7], average RSS variation due to Wi-Fi nodes heterogeneity may exceed 18 dBm. Authors compared RSS of notebook and smartphone from the same location and at the same Wifi access point. They prove that the average RSS value from notebook is -47,6dBm whereas from the smartphone is -

66.2 dBm. Another experiment done in [8] also supports this result. To overcome localization error induced due to RSS variation, one of our motivations is to find the locations of unknown nodes in a certain wireless area with different hardware configurations.

On the other hand, the major drawback of fingerprinting localization is dependence on offline stage (or training stage). It consumes more time and labor during the collection of signal strength data and a huge volume of data needs to be stored as fingerprinting. Positional accuracy of this algorithm is positively associated with the density of anchor points in the database.

In this paper, we propose a method to locating an unknown node or user in indoor wireless networks not only without using offline stage but also independence on hardware parameters.

The remainder of the paper is organized as follows: an overview of the well-known indoor localization techniques is presented in Section II. Section III presents our algorithm. Finally, in section IV we discuss some limitations, future works and conclude the work of this paper.

II. RELATED WORK

Internet of Things merge many different technologies, like Zigbee, Internet, Infrared, Bluetooth, 3G, GPRS, Wi-Fi, etc… that will help in identifying the location of various objects. However, it is difficult to equip each node of the IoT with a positioning device in real world. Instead, only a few nodes, called anchors, know their positions. Other nodes estimate their distances to a few nearby (neighbor) nodes, determine the position coordinates of every node via local node to node communication. Otherwise, wireless communication system is the essential part for IoT infrastructure. In some extent, positioning in IoT can refer to previous research paradigms for localization in wireless network. For solving wireless indoor localization problem, there is a variety of well-known research directions, many methods have been proposed. Hence, we mainly review these schemes. They may be classified into two categories, namely, fingerprinting-based and model-based.

The concept of fingerprinting localization has the same concept as human fingerprinting. To constitute a fingerprint, several types of information can be used as the received signal strength (RSS), angular power profile (APP) and channel impulse response (CIR). Almost fingerprinting-based localization techniques consist of two stages: offline (or offline) stage and online (or serving) stage. In the first stage, they build a fingerprint database by recording the signal metrics (fingerprints) received at every position of an interesting area. This process is also called site survey. During the online stage, when a node sends a location query with its current fingerprint, location positioning techniques retrieve the fingerprint database and then mapping the collected fingerprints against the database to estimate the location as shown in Figure 2. The RADAR system [9] was the world's first RSS fingerprinting based indoor positioning. Bahl and Padmanabhan prove that RF fingerprinting and environmental profiling with commodity wireless LAN hardware can be used to determine user and machine location inside buildings, thereby enabling indoor location-aware applications. Radio Camera system [10] uses multipath angular power profile (APP) information gathered at one receiver to locate the user's coordinates. Meurer [11] proposed using the covariance matrix of the CIR as a location fingerprint to locate and track mobile units. An advantage of fingerprinting localization is to obtain optimal performance in multipath environment. Using fingerprinting consumes more time and labor during the collection of signal strength data and a huge volume of data needs to be stored as fingerprinting depends on a pre-existing signal strength database for all anchor points. Positional accuracy with a fingerprinting algorithm is positively associated with the density of anchor points in the database. Too few features selected for the fingerprint may not give sufficient information to differentiate the various locations of interest, while too many features may include bad features that are unstable in time, causing the system to produce poor results.

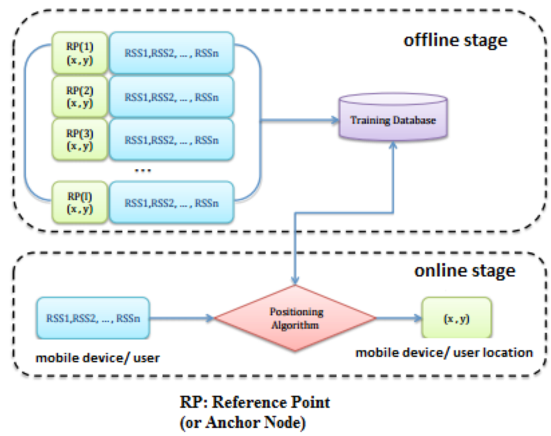

Figure 2. The diagram of RSS based fingerprinting localization technique

To alleviate this problem, wireless indoor localization approach based on model has been introduced. This algorithm does not need an offline stage like fingerprinting. Propagation model based methods use mathematical models to predict the distance between transmitter and receiver based on the power with which a packet sent by a transmitter reaches the receiver. From this information, it is possible to estimate the position of the receiver by geometric computations (e.g., trilateration). The angle of arrival (AOA)-based positioning technique [12] measures the angles between a given node and a number of anchor nodes to determine the location of a node. Upon on a path-loss model, the RSS-based localization measures the energy of the received signal at one node to calculate the distance between two nodes. Time-based positioning techniques rely on measurements of travel times of signals between nodes. If two nodes have a common clock, the node receiving the signal can determine the time of arrival (TOA) of the incoming signal that is time-stamped by the anchor node [13]. As shown in Figure 3, TOA based positioning measurements must be made with respect to signals from at least three anchor points. If there is no synchronization between a given node and the anchor nodes, but there is synchronization among the anchor nodes, then the time-difference-of-arrival (TDOA) technique can be employed [14].

Therefore, these techniques are more flexible as the system calculates node location in real-time (no offline stage is needed) and the system can be more adaptable to environmental change than fingerprinting. However, in the fact, it is not easy to model the radio propagation in the indoor environment. The inaccuracy of this approach is mainly due to the propagation conditions imposed by the wireless channel as multipath and non-line of sight (NLOS) conditions, floor layout, moving objects, and numerous reflecting surfaces.

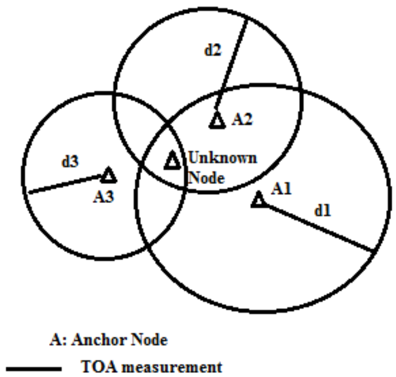

Figure 3. The TOA based localization technique

In this section, we also demonstrate the dependence of RSS on hardware configurations. From the log-normal shadowing model [15], ignoring the variation of the received power at a certain distance, we get:

$$\left[\frac{P(d)}{P(d_0)}\right]_{dB} = -10\beta\log\left(\frac{d}{d_0}\right) \qquad (1)$$

Where,

- $P(d)$ is the received signal strengths at an arbitrary distance of d in dB;
- $P(d_0)$ is the received signal strengths at close-in reference distance of d0 in dB;
- d is the distance between the transmitter and the receiver in meters;
- d_0 is the reference distance in meters, typically 1m in the indoor environment;
- β is the path loss exponent in dB/meter

Eqn. (1) can be rewritten as,

$$P(d)|_{dBm} = P(d_0)|_{dBm} - 10\beta\log\left(\frac{d}{d_0}\right) \quad (2)$$

Since the perceived power at a reference distance $P(d_0)$ varies because of antenna gains (hardware-specific parameter). Therefore, the perceived RSS at a distance d is also hardware-dependent. Although RSS is the most favorite information used in existing RSS based fingerprinting techniques, but almost these did not address this issue.

Through above brief summary, we can see that each approach has its advantages and limitations. The choice of technique and technology significantly affects the granularity and accuracy of the location information. To solve this problem, we propose a new algorithm which can be independent of radio propagation parameters without offline stage.

III. PROPOSED ALGORITHM

The purpose of this section is to investigate a new algorithm which is simple technique to estimate position of an unknown node or user in an interesting wireless area.

Many of the existing location fingerprinting methods lack a proper mathematical formulation and theoretical basis. By using mathematical analysis, we demonstrate that our method does not require offline stage. Moreover, the proposed technique does not depend on radio propagation parameters such as path loss and hardware-specific parameters like antenna gains.

In the IoT, nodes can be deployed in a two or three dimensional space. To simplify the explanation, we assume that they are deployed in a two-dimensional space in the rest of the paper. Whether the distribution of nodes is random or not, the nodes should be able to communicate with neighbours that are in a range of radio range.

We denote the location of unknown node/ user which receives signal from n anchors as (x, y) in its broadcast range as described in Figure 4.

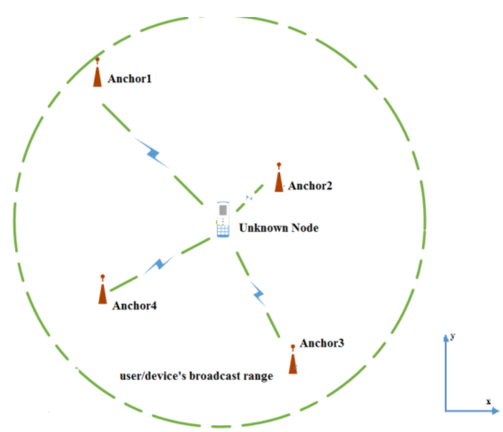

Figure 4. Wireless Network Topology

We assume the coordinates of n anchors are already given as:

$$Anchor_1 = (x_1, y_1)$$
$$Anchor_2 = (x_2, y_2)$$

$$\ldots Anchor_n = (x_n, y_n)$$

Among n anchors which can receive signal from that unknown node/ user, we choose k anchors (k<n) with bigger RSS values:

$Anchor_1$, $Anchor_2$, …, $Anchor_k$

Let d_i is the distance between unknown node/user and the i Anchor (i=1,..k). We have:

$$\sqrt{(x - x_i)^2 + (y - y_i)^2} = d_i \qquad (3)$$

Squaring both side and giving k anchors, we have the following set of equations will be true with every i, assume that have no estimation error for the moment:

$$\begin{cases} (x - x_1)^2 + (y - y_1)^2 = d_1^2 \\ (x - x_2)^2 + (y - y_2)^2 = d_2^2 \\ \ldots \\ (x - x_k)^2 + (y - y_k)^2 = d_k^2 \end{cases} \qquad (4)$$

Expand the elements on the left and after that subtracting the bottom row from each of remaining rows, then moving all remaining square terms to the right hand side. As a result, above equation can be written again:

$$\begin{cases} 2(x_k - x_1)x + 2(y_k - y_1)y = d_k^2 - d_1^2 + x_k^2 - x_1^2 + y_k^2 - y_1^2 \\ 2(x_k - x_2)x + 2(y_k - y_2)y = d_k^2 - d_2^2 + x_k^2 - x_2^2 + y_k^2 - y_2^2 \\ \ldots \\ 2(x_k - x_{k-1})x + 2(y_k - y_{k-1})y = d_k^2 - d_{k-1}^2 + x_k^2 - x_{k-1}^2 + y_k^2 - y_{k-1}^2 \end{cases} \qquad (5)$$

Equation (5) can be written in matrix form as:

$$\begin{bmatrix} 2(x_k - x_1) & 2(y_k - y_1) \\ 2(x_k - x_2) & 2(y_k - y_2) \\ \ldots & \\ 2(x_k - x_{k-1}) & 2(y_k - y_{k-1}) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} d_k^2 - d_1^2 + x_k^2 - x_1^2 + y_k^2 - y_1^2 \\ d_k^2 - d_2^2 + x_k^2 - x_2^2 + y_k^2 - y_2^2 \\ \ldots \\ d_k^2 - d_{k-1}^2 + x_k^2 - x_{k-1}^2 + y_k^2 - y_{k-1}^2 \end{bmatrix} \qquad (6)$$

On other hand, the relationship between RSS and distance is also described in the following equation:

$$P(d_i)\Big|_{dBm} = P(d_0)\Big|_{dBm} - 10n\log\left(\frac{d_i}{d_0}\right) \qquad (7)$$

Moving all received signal strength to one side and getting log logarithm two both sides, we have:

$$d_i = 10^{\frac{P(d_0) - P(d_i)}{10n}} \qquad (8)$$

After squaring both sides, resulting as:

$$d_i^2 = 10^{\frac{P(d_0) - P(d_i)}{5n}} \qquad (9)$$

Applying Taylor expansion to (9), we get:

$$d_i^2 = 10^{\frac{P(d_0) - P(d_i)}{5n}} \approx C_0 + C_1\left(\frac{P(d_0) - P(d_i)}{5n}\right) \qquad (10)$$

where, C_0, C_1 is the coefficients

Combining equations (9) and (10):

$$d_k^2 - d_i^2 = \frac{C_1}{5n}(P(d_k) - P(d_i)) \qquad (11)$$

From (6) and (11), we have:

$$\begin{bmatrix} 2(x_k - x_1) & 2(y_k - y_1) \\ 2(x_k - x_2) & 2(y_k - y_2) \\ \ldots & \\ 2(x_k - x_{k-1}) & 2(y_k - y_{k-1}) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \frac{C_1}{5n}(P(d_k) - P(d_1)) + x_k^2 - x_1^2 + y_k^2 - y_1^2 \\ \frac{C_1}{5n}(P(d_k) - P(d_2)) + x_k^2 - x_2^2 + y_k^2 - y_2^2 \\ \ldots \\ \frac{C_1}{5n}(P(d_k) - P(d_{k-1})) + x_k^2 - x_{k-1}^2 + y_k^2 - y_{k-1}^2 \end{bmatrix} \qquad (12)$$

Equation (12) can be rewritten as follows:

$$\begin{bmatrix} 2(x_k - x_1) & 2(y_k - y_1) & (P(d_k) - P(d_1)) \\ 2(x_k - x_2) & 2(y_k - y_2) & (P(d_k) - P(d_2)) \\ \ldots & & \\ 2(x_k - x_{k-1}) & 2(y_k - y_{k-1}) & (P(d_k) - P(d_{k-1})) \end{bmatrix} \begin{bmatrix} x \\ y \\ \frac{C_1}{5n} \end{bmatrix} = \begin{bmatrix} x_k^2 - x_1^2 + y_k^2 - y_1^2 \\ x_k^2 - x_2^2 + y_k^2 - y_2^2 \\ \ldots \\ x_k^2 - x_{k-1}^2 + y_k^2 - y_{k-1}^2 \end{bmatrix} \qquad (13)$$

Let denote:

$$z = \frac{C_1}{5n} \qquad (14)$$

We achieve:

$$\begin{bmatrix} 2(x_k - x_1) & 2(y_k - y_1) & P(d_k) - P(d_1) \\ 2(x_k - x_2) & 2(y_k - y_2) & P(d_k) - P(d_2) \\ \ldots & & \\ 2(x_k - x_{k-1}) & 2(y_k - y_{k-1}) & P(d_k) - P(d_{k-1}) \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x_k^2 - x_1^2 + y_k^2 - y_1^2 \\ x_k^2 - x_2^2 + y_k^2 - y_2^2 \\ \ldots \\ x_k^2 - x_{k-1}^2 + y_k^2 - y_{k-1}^2 \end{bmatrix} \qquad (15)$$

Equation (15) is a matrix equation:

$$AX = B$$

In which, values in A and B have already known.

We can see that: equation (15) doesn't depend on hardware parameters and it just depends on the coordinates of known anchors and their received RSSs. In other words, estimation of unknown node/ user location doesn't depend on radio propagation parameters and hardware-specific parameters.

Through above analysis, we can see that our proposed scheme eliminates the need of acquiring reference RSS measurements and the offline stage. As a result, the localization is performed quickly. Moreover, the estimation of unknown node is independent on radio propagation parameters such as path loss and hardware-specific parameters such as antenna gains.

IV. CONCLUSIONS

As the penetration of the IoT goes up rapidly, more and more devices are getting wirelessly connected to the Internet. These devices come from many different vendors with different technologies. However, almost existing localization solutions have not address to heterogeneous devices yet. On the other hand, previous indoor localization approaches mostly rely on labour - intensive site survey over every location or factors of wireless indoor environment. This paper innovatively proposes an indoor wireless positioning algorithm for localization in the IoT. The proposed scheme is independent on radio propagation parameters, hardware-specific parameters and no offline stage is needed. By using mathematical formulation analysis, we demonstrate its advantage than the others.

For our future works, we plan to implement our algorithm in the real wireless environment or using networks simulation and investigate different estimation techniques to fide the more accurate node location.

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