Proxy Individual Positioning via IEEE 802.11 Monitor Mode and Fine-tuned Analytics

Myungsung You and Soochang Park
Dept. of Computer Engineering
Chungbuk National University
Cheongju, Republic of Korea
{famous and cewinter}@chungbuk.ac.kr

Sang-Hoon Lee
Dept. of Management Information Systems
Chungbuk National University
Cheongju, Republic of Korea
leshun@chungbuk.ac.kr

Taehun Yang
Dept. of Computer Engineering
Chungnam National University
Daejeon, Republic of Korea
thyang@cclab.cnu.ac.kr

***Abstract*—Indoor positioning of individuals is one of the most important technologies in smart home applications for user-customized support. The indoor positioning is typically fulfilled through radio signal strength indicators (RSSIs) of referred devices with specific media such as Wi-Fi access points (APs) and Wi-Fi station devices (STAs). So, the capability of typical positioning schemes is highly close to the signal acquisition environments of such media. In other words, since STAs frequently fall into a sleep mode to save the battery power and some data acquisition technologies are based on advertising intervals, the amount of RSSIs of referring devices could not be gathered enough to detect correct positions of individuals. In this paper, a novel individual positioning mechanism, called PIPing (Proxy Individual Positioning), is come up with. The PIPing mechanism carries out proxy signal acquisition via IEEE 802.11 monitor mode devices to overcome such restrictions. In addition, PIPing includes machine learning based signal data analytics to provide high reliable results for positioning. Based on the proof-of-concept prototype, PIPing can acquire much higher amount of RSSI data than existing manners, about 330% increment; the reliability of positioning for a home with seven rooms shows 96.4% via the support vector machine (SVM) and 96.5% by the multilayer perceptron (MLP) with autoencoder denoising to tune up signals.**

***Index Terms*—Indoor Positioning, Internet-of-Things, Smart Home Applications**

I. Introduction

Smart home applications mainly provide user-customized automation of home appliance or energy saving based on the presence of home members [1]- [4]. For such applications, the indoor positioning of individuals with high accuracy is the most important technology. The indoor positioning technologies are relied on the radio signal strength indicators (RSSIs) of referred devices running specific media like Wi-Fi or Bluetooth Low Energy (BLE). In other words, when a user carries a smart mobile device with the media Wi-Fi and BLE, the smart mobile device of the user receives RSSIs from several static devices as referred points to measure the location of the smart mobile device. So, the quantity of RSSIs of the referred devices is one of key factors to get highly accurate and reliable location of the smart mobile device, i.e., the user.

Typically, indoor localization technologies based on RSSIs of referred points could be classified to two strategies: 1) host-based approach and 2) network-based approach. First, in the host-based approach, the host node such as a smart mobile device of a user involves positioning measurement. So, the smart mobile device acquires RSSIs from referred devices, and then it asks the location of itself to the cloud where the whole RSSI fingerprint map is existed. The smart mobile device eventually get its location from the cloud. On the other hand, the network-based approach relies on the monitoring (sometimes, sniffing) by network nodes in terms of host nodes like smart mobile devices of users. Thus, network nodes receive RSSIs from a smart mobile device and they could measure the position of the device. Namely, the second approach by network node based monitoring could provide transparency to the host nodes, i.e., users.

Due to the privacy concern and installation/operation costs, the use of the host-based localization might be unacceptable for many people in various service domains. In recent years, Wi-Fi has gained tremendous popularity at residential homes and even Internet-of-Things (IoT) home appliance [4]. At the present time, it is not unusual to detect tens of Wi-Fi signals in an apartment building or a private residence in an urban site. Rather than being wasted, these readily available sources of information can be used to perform indoor localization because the signal strength reduces with the distance and obstacles. The aim of these researches is to gain a better understanding of the indoor localization method via such off-the-shelf devices to monitor Wi-Fi signals and answer a critical question whether the RSSI signal itself is sufficient to localize specific rooms in a multi-room complex.

However, existing researches have restrictions to achieve high level accuracy for localization since smart mobile device frequently falls into a sleep mode for energy efficiency and the advertisement intervals for message broadcasting which can be caught as RSSIs are not long enough to measure correct position of itself. So, this paper proposes a novel indoor positioning mechanism relying on network-based RSSI monitoring with the monitor mode of IEEE 802.11 specification, so-called proxy individual positioning (PIPing). PIPing can overcome those restrictions through the Address Resolution Protocol (ARP) request message or the Internet Control Message Protocol (ICMP) request message. In addition, to achieve high level accuracy of positioning, PIPing relies on machine learning technologies, i.e., the support vector machine (SVM), the multilayer perceptron (MLP), and the autoencoder. The experimental results based the proof-of-concept implementation

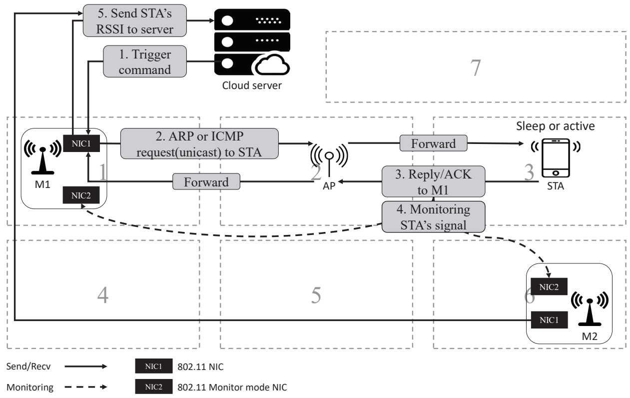

Fig. 1. System Architecture

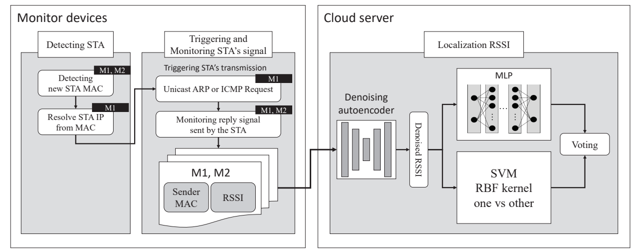

Fig. 2. PIPing Framework Architecture

show that PIPing can provide positioning accuracy with 96.4% via SVM and 96.5% by MLP after fine-tuning signal data sets through the autoencoder based denoising.

II. Related Work

In this section, we explore the existing researches related to indoor positioning mechanisms based on IEEE 802.11 standard. The most of the indoor positioning mechanisms use the wireless signal information, like Wi-Fi RSSIs. There are three mechanisms to obtain Wi-Fi signal information: STA active scan, STA passive scan, and RTS/CTS Handshake.

The beacon frame based positioning is a mechanism that the STA obtains Wi-Fi signals of a number of around APs, which are advertising the beacon frame periodically [5] [6] [7]. For this, this mechanism requires an additional cost, that a dedicated software program for scanning Wi-Fi signals has to installed on the STA. Besides, the STA has the limitation for obtaining Wi-Fi signals. To get a high accuracy for localization, it needs a large number of the signals. Thus, the STA should collect the signals as many as possible. However, this mechanism is inefficient for signal acquisition. Because the collision and interference are occurred by the nature of the wireless medium and the scan interval of the STA is slower than the advertisement interval of the AP [4].

In contrast, there is the probe request based positioning using Wi-Fi active network scanning [8] [9] [10] [11]. A STA advertises a probe request frame periodically, and it requires to discover the existence of APs. In this environment, the probe request mechanism may be suitable for getting RSSIs for indoor positioning. Also, this mechanism does not need to set up the software program, unlike the beacon frame based positioning. However, it does not support consecutive positioning since the STA only advertises a probe request frame while the STA works network scanning. On the other hand, this positioning mechanism does not work if the STA is sleep mode. In addition, it requires a long time since the advertisement interval of a probe request frame is long.

Finally, RTS/CTS (Request to Send / Clear to Send) based positioning is similar to aforementioned mechanisms. For the indoor localization, it uses frames of RTSCTS handshaking [12] [13] [14]. RTS/CTS is the optional mechanism used by the 802.11 wireless networking protocol to reduce frame collisions introduced by the hidden node problem. So, receiving a RTS frame, all STAs send a CTS frame in this mechanism. According to this procedure, this mechanism is highly efficient for a number of RSSIs in a short time [12]. However, the STA in sleep mode cannot receive any RTS frame. That is, the STA cannot obtain the RSSI.

In consequence, existing mechanisms to gether RSSIs from APs or STA have some restrictions regarding to impossibility during the sleep mode and advertising intervals of messages related to RSSIs. Therefore, this paper comes up with a novel positioning mechanism with a solution to overcome such restrictions, named PIPing.

III. PIPing: Proxy Individual Positioning

This section explains the architectural overview for the PIPing mechanism with core message exchanges in brief. Also, considerable issues are presented with their solutions involved in PIPing mechanism.

A. System Architecture

PIPing is composed of a cloud server for analytics, a AP (IEEE 802.11 access point), a STA (IEEE 802.11 station node) which is a target device to measure localization, and two or three monitoring nodes running in the IEEE 802.11 monitor mode, denoted by M1 and M2. PIPing estimates locations of the STA through room-level indoor positioning with high accuracy and reliability. The monitor devices M1 and M2 use an IEEE 802.11 NIC (network interface card) and an Monitor mode NIC. They communicate with the cloud server and sniff frames sent by the STA.

TABLE I
PIPing and Other methods

	Beacon	Probe request	RTS-CTS	PIPing
Frame scanning rate	Very slow (1 frame / every 4sec)	Slow (10 frames / every 10 sec)	Fast	Very Fast
Additional App install	O	X	X	X
Sleep mode	O	X	X	O

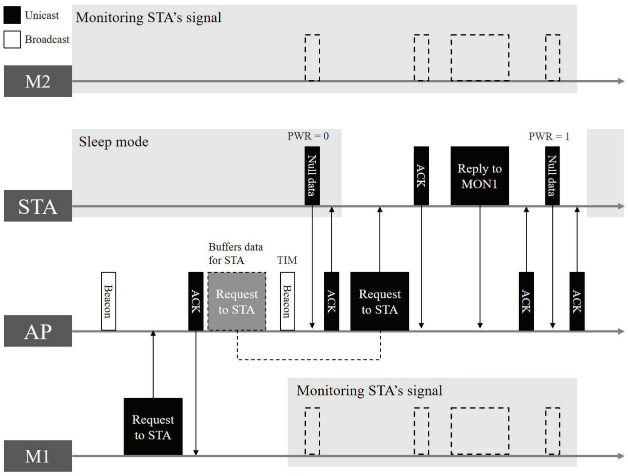

Fig. 3. PIPing Timing Diagram

As shonw in Fig. 1, firstly the cloud server sends the trigger command to M1, and then M1 transmits a ARP or ICMP request message to the STA through AP. AP relays the request message to the STA, and then the STA replies an ACK message to M1 via the AP. During such message exchanging, M1 and M2 are able to catch those messages by their IEEE 802.11 Monitor mode NIC.

Based on the monitored message, PIPing can acquire RSSI information related to the STA that is utilized for RSSI based positioning. PIPing relies on two machine learning technologies: SVM and MLP algorithms.

B. Considerable Issues and Solutions

In the beacon based positioning, RSSI scanning interval of STA is slow to investigate indoor positioning. However, PIPing get a lot of RSSI faster than the beacon based positioning in short time. Unlike the beacon based mechanism which is easily suffer from beaconing environment change, PIPing can seamlessly gather RSSIs since it continuously regather signals if the receiving amount of RSSIs is reduced due to environmental situations.

Meanwhile, in the probe request based positioning and the RTS/CTS based positioning, STA can not get a RSSI in sleep-mode. Thus, STA can not investigate indoor positioning. However, PIPing can investigate indoor positioning in sleep-mode of STA. The monitor devices of PIPing send ARP request or ICMP request to the STA, and the STA sends reply frame. Then, the monitor devices sniff the RSSI of STA.

IV. PIPing Operation

A. Framework Architecture

PIPing's system operation consists of the two steps. First, the system identifies the STA and obtains the RSSI. Second, predicting the indoor positioning with the RSSI is performed using the support vector machine (SVM) and multilayer perceptron (MLP).

B. Detecting New STA and Collecting Data

In the proposed system, the monitor devices $M1$ and $M2$ sniff IEEE 802.11 frames NIC through IEEE 802.11 monitor mode NIC. The monitor devices check the target STA using the MAC address of the sniffed IEEE 802.11 frame. STA is checked by the monitor devices, $M1$ sends ARP or ICMP request to STA. Then, STA in non sleep mode receives ARP or ICMP request and sends ARP or ICMP reply to the $M1$. In the sleep mode of STA, AP inserts the request of $M1$ to buffer. Then, the AP indicates the buffered frame in the beacon frame. STA receives this beacon frame, sends a null data frame to AP and wakes up in sleep mode. AP sends the buffered frame and STA sends ARP reply to $M1$. Finally, STA sends a $null$ data to AP and back to the sleep mode.

C. Denoising and Positioning

The RSSI sent to the server contains some fluctuated values due to the nature of the wireless medium. Fig. 4. shows RSSI obtained from three monitors in the room 1, 2 and 6. Fluctuate values are not clustered and are scattered. These values are filtered through denoising autoencoder. Fig. 5. shows the result of the denoising autoencoder and most of the fluctuated values has disappeared. In order to indoor localization, SVM and

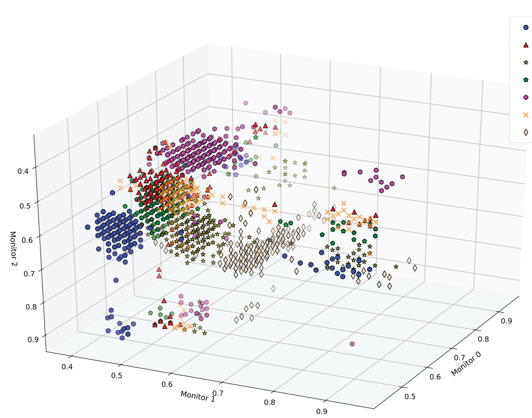

Fig. 4. Raw RSSI with 3 monitors

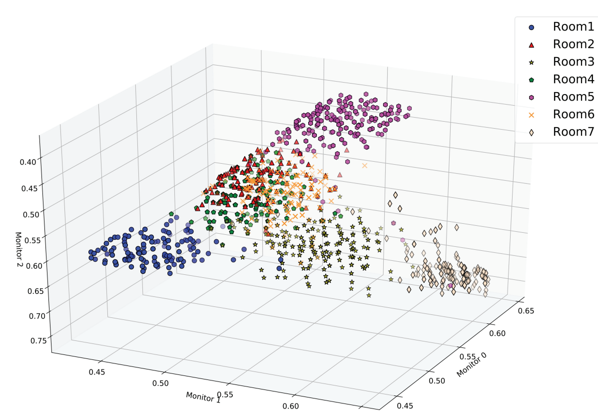

Fig. 5. Denoised RSSI with 3 monitors

Room	1	2	3	4	5	6	7	Recall
1	1276	0	3	0	0	0	0	1.00
2	0	1124	1	43	6	82	0	0.89
3	5	2	1225	7	2	4	0	0.98
4	6	42	5	1211	0	6	0	0.95
5	0	3	1	2	1226	0	1	0.99
6	0	52	15	4	2	1165	0	0.94
7	2	2	1	1	1	0	1222	0.99
Precision	0.99	0.92	0.98	0.96	0.99	0.93	1.00	

Fig. 6. Confusion Matrix of SVM with 2 monitors

Room	1	2	3	4	5	6	7	Recall
1	1265	0	4	10	0	0	0	0.99
2	0	1130	2	24	13	87	0	0.90
3	5	0	1225	10	2	2	1	0.98
4	12	67	5	1180	1	5	0	0.93
5	0	11	4	1	1214	2	1	0.98
6	1	46	11	5	17	1158	0	0.94
7	0	2	13	0	0	0	1214	0.99
Precision	0.99	0.90	0.97	0.96	0.97	0.92	1.00	

Fig. 7. Confusion Matrix of SVM with 3 monitors

Room	1	2	3	4	5	6	7	Recall
1	1260	0	4	15	0	0	0	0.99
2	0	1115	2	35	16	88	0	0.89
3	5	0	1223	10	0	2	5	0.98
4	31	68	6	1162	0	3	0	0.91
5	0	10	4	2	1212	4	1	0.98
6	0	39	11	11	15	1162	0	0.94
7	0	0	17	0	0	0	1212	0.99
Precision	0.97	0.91	0.97	0.94	0.98	0.92	1.00	

Fig. 8. Confusion Matrix of MLP with 2 monitors

Room	1	2	3	4	5	6	7	Recall
1	1274	0	3	2	0	0	0	1.00
2	0	1115	2	46	6	87	0	0.89
3	0	0	1222	14	2	2	5	0.98
4	6	35	8	1217	0	4	0	0.96
5	0	2	0	2	1225	1	3	0.99
6	0	47	12	5	3	1171	0	0.95
7	0	0	2	0	4	0	1223	1.00
Precision	1.00	0.93	0.98	0.95	0.99	0.93	0.99	

Fig. 9. Confusion Matrix of MLP with 3 monitors

MLP are performed using the RSSI. SVM used RBF kernel and MLP has three hidden layers. Finally, PIPing predicts the indoor position of the STA by hard voting the two results.

V. Performance Evaluations

A. Experimental Design

The experiment was conducted at seven different rooms. The size of rooms 1 to 6 is 3m x 2.5m and room 7 is 6m x 3m. we used monitor devices for Raspberry Pi 3B+ with ipTIME N150UA WNIC. Room 1 and 6 have two monitor devices. Room 1, 2 and 6 have three monitor devices to collect the data. 70,000 data were measured in room 1 and 6. 100,000 data were measured in room 1, 2 and 6.

B. Experimental Results

To distinguish the seven rooms, it is experimented with two to three monitor devices. We analyzed the performance evaluation using two machine learning techniques: SVM and MLP with the RSSI obtained from the monitor devices. The same data is used on both machine learning techniques. Both of the accuracy of indoor positioning was higher using three monitor devices than using two monitor devices. Because the higher the number of monitor devices, the more RSSI collected from the monitor devices. Finally, the number of data increases the performance of machine learning technology. Therefore, as the number of monitors increases, the amount of data.

TABLE II
Training Time Table

	2 Monitor	3 Monitor
SVM	26729ms	4098ms
MLP	341536ms	332067ms

TableII shows the learning time of machine learning according to the number of monitors. MLP has no learning time difference according to the number of monitors. However, SVM using three monitors is 6.5 times better than SVM using two monitors. Fig.10 shows the learning time of the SVM according to the amount of data. Using the same data, SVM's speed is about 81 times faster than MLP's speed. SVM is better than MLP to learn a large number of Wi-Fi RSSI.

Fig.11 shows the RSSI collected for 35 seconds using PIPing and three other methods. We used Samsung Galaxy S6 as STA. PIPing is set up to send an ARP request to the STA every 0.5 seconds. The RTS/CTS is set up to send the RTS frame to STA every 0.25 seconds. The total of collected frames is 210 for PIPing, 20 for probe request, 11 for beacon and 160 for RTS/CTS, repectively. The STA sent 10 probe requests

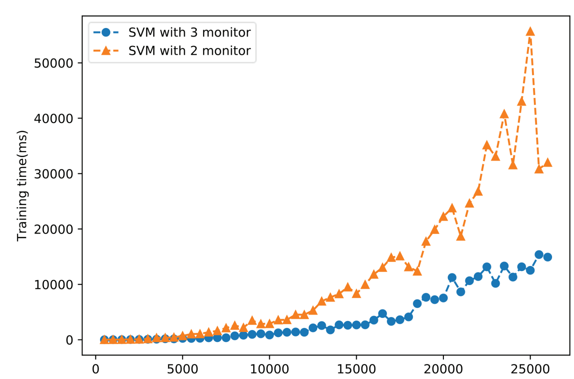

Fig. 10. Training time of SVM

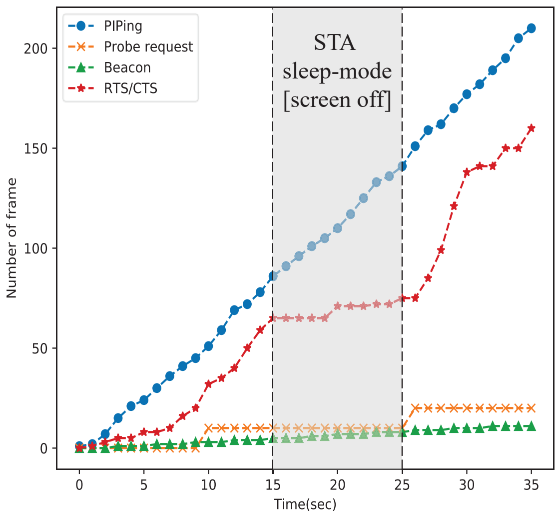

Fig. 11. PIPing vs Other methods

every 10 seconds. Probe request and RTS/CTS methods is difficult to collect RSSIs. Finally, PIPing and beacon based positioning were not affected by sleep mode. Beacon based positioning obtained 11 RSSIs and PIPING obtained 210 RSSIs. It is possible to obtain more RSSIs by shortening the ARP request interval.

VI. Conclusion and Future Work

This paper proposes a novel indoor individual positioning mechanism, denoted by proxy individual positioning (PIPing). To overcome previous works, PIPing relies on ARP and ICMP request messages to acquire RSSIs of STAs during the sleep state of STAs. In addition, PIPing is not dependent of the advertising intervals. So, PIPing can gather large enough data sets to achieve high level accuracy of localization of STAs rapidly. The experimental results via the proof-of-concept show that PIPing can provide positioning accuracy with 96.4% via SVM and 96.5% by MLP with autoencoder denosing. In the future, we will optimize request sending intervals to reduce overhead on the network and gather enough date sets.

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