Design of WiFi-AP Operating Channel Estimation Scheme for Sensor Node

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***Abstract*—Sensor localization is one of the big problems when building large scale indoor sensor networks because GPS (Global Positioning System) is unavailable in indoor environments. We are developing a sensor localization system using WiFi APs as anchors, which requires no anchor deployment. Because sensor nodes cannot demodulate WiFi signals, we have developed a cross-technology RSS (received signal strength) measurement scheme with an AP recognition scheme [1, 2].**

In this paper, we present WiChest, a WiFi-AP operating channel estimation scheme to accurately measure AP-RSS on sensor nodes. A WiFi channel overlaps with four ZigBee channels. AP-RSS depends on a ZigBee channel in which a sensor node measures the RSS. Using WiChest, a sensor node automatically switches its channel based on an estimated AP channel prior to RSS measurement. We implemented WiChest using a MICAz sensor node. The experimental evaluations reveal that WiChest accurately estimates AP operating channels with an F-measure of 0.80.

***Index Terms*—WiFi-AP anchors, sensor localization, operating channel, cross-technology signal detection.**

I. Introduction

Sensor network is gaining its importance due to its low-cost and low-power features in the fields of M2M (Machine-to-Machine) communications, IoT (Internet of Things), and CPS (Cyber Physical Systems). In sensor networks, sensor location is important information used for recognizing sensing area, target tracking, and network building. Large scale indoor sensor networks face a sensor localization problem; we need to localize a huge number of sensor nodes by hand because GPS (Global Positioning System) is unavailable in indoor environments.

To address the sensor localization problem, previous studies have reported sensor localization systems [3–5]. Although these studies have successfully reduced deployment costs [6–15] or improved accuracy [16–22], they require user cooperation or anchor nodes whose location is manually measured.

We are developing an indoor sensor localization system using WiFi APs as anchors, which requires neither user cooperation nor anchor deployment. Figure 1 depicts an overview of the sensor localization system using WiFi APs as anchors. WiFi APs are largely installed in many indoor environments and their locations are managed by a network system manager. We send specific signals from multiple WiFi APs and measure RSS (received signal strength) of the AP signals on sensor nodes. Sensor location is calculated from the RSS of multiple APs using an RSS-based localization scheme such as multilateration.

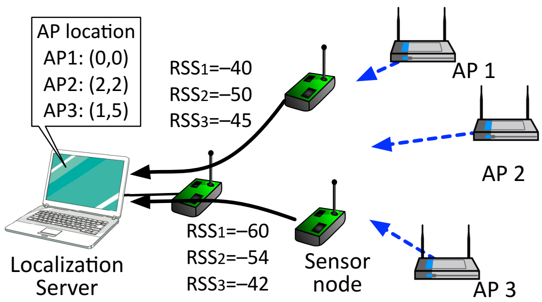

Fig. 1. Overview of a sensor localization system using WiFi APs as anchors

In our previous papers, we have reported a WiFi AP-RSS measurement scheme [1] as well as an AP recognition scheme [2] using sensor nodes. Sensor nodes are equipped with ZigBee (IEEE 802.15.4) modules and cannot demodulate WiFi (IEEE 802.11) signals. We therefore developed a cross-technology signal extraction scheme. We experimentally demonstrated that our AP-RSS measurement scheme successfully measured AP-RSS with an average error of 1.26 dB and an AP recognition error less than 10 %.

However, AP-RSS measured on a sensor node is affected by a WiFi-AP operating channel and the sensor node observation channel. Each WiFi channel overlaps with four ZigBee channels. Sensor nodes observe different RSS of an identical WiFi signal in different ZigBee channels.

To accurately measure AP-RSS on sensor nodes, this paper presents WiChest, a WiFi-AP operating channel estimator. The WiChest is based on an observation that WiFi signals are detected by sensor nodes in four ZigBee channels that depend on the WiFi operating channel. We detect WiFi-AP signals in multiple ZigBee channels and estimate the WiFi operating channel based on the ZigBee channels where AP signals are detected. Many WiFi APs automatically select their operating channels to reduce communication errors. Using WiChest, sensor node can automatically switch its ZigBee channels prior to RSS measurement. We implemented and evaluated WiChest using a MICAz sensor node to demonstrate the basic performance.

Specifically, our main contributions are twofold:

- We present the design of WiChest, a WiFi-AP operating channel estimator for sensor nodes employing ZigBee (IEEE 802.15.4) modules. To the best of our knowledge,

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this is a first attempt to estimate a WiFi operating channel using sensor nodes employing ZigBee modules.
- We show basic performance of the WiChest by experimental evaluations using an actual sensor node and WiFi APs.

The remainder of this paper is organized as follows. Section II briefly describes related works and Section III presents the design of WiChest. In Section IV, we conduct experimental evaluations to show the basic performance of the WiChest. Finally, Section V concludes the paper.

II. Related Works

To the best of our knowledge, WiFi operating channel estimation on sensor nodes is novel in the field of sensor networks. In this section, we look through related works on indoor sensor localization and WiFi signal detection using sensor nodes.

A. Indoor Sensor Localization

In the field of indoor localization, previous studies have primarily investigated reduction in deployment costs or accuracy improvement. Most of these works are using WiFi devices, which still can be applied to sensor nodes employing ZigBee modules.

Iterative multilateration [6, 7] uses localized nodes as new anchor nodes, which reduces the number of initial anchor nodes. However, many initial anchors are still required to achieve small localization error in large scale sensor networks. Crowdsourcing combined with fingerprinting localization [8–15] is another approach that reduces deployment costs. For a sensor localization system, it is difficult to get user cooperation because almost all users are carrying no ZigBee devices.

Our paper does not aim to improve accuracy because existing localization algorithms can be easily employed to our localization system. Previous works on accuracy improvement [16–22] is therefore useful for our goal, i.e., sensor localization using WiFi APs.

There is a new fingerprinting localization named ZiFind that requires no anchor nodes [23]. ZiFind, however, requires many WiFi devices called ZiFind mappers instead of anchor nodes.

B. WiFi Signal Detection using Sensor Nodes

We categorize WiFi signal detection schemes using sensor nodes into two groups by a research objective: for cross-technology interference avoidance and for cross-technology communication.

For cross-technology interference avoidance, ZiFi enables sensor nodes to detect WiFi-AP signals [24]. WiFi APs are periodically sending beacon signals in their operating channels. Sensor nodes detect the periodic beacon signals using a simple signal processing technique. Although ZiFi enables sensor nodes to detect WiFi APs, the AP operating channels are unknown. TIIM provides a machine learning classifier to determine cross-technology interference sources [25]. ZigBee network chooses the best coexistence mitigation strategy that depends on an interference pattern. TIIM provides no method to estimate an operating frequency of the interference source because the operating frequency has no effect on the choice of the strategy.

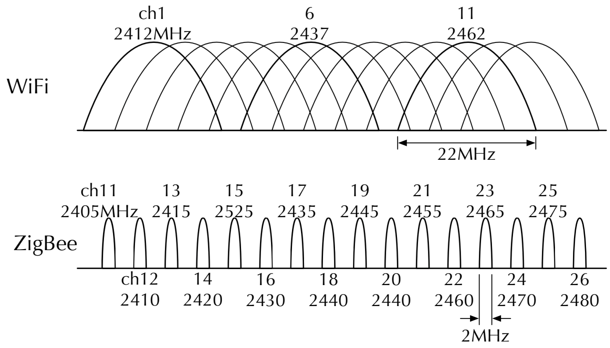

Fig. 2. WiFi and ZigBee channels

For cross-technology communication, Esense provides communication based on WiFi frame length, which can be measured on sensor nodes [26, 27]. To distinguish WiFi signals from WiFi devices out of the Esense system, Esense statistically analyzes WiFi frame lengths and uses rarely used signal length. FreeBee is a kind of PPM (pulse position modulation) using beacon signals [28]. Beacons are shifted by specific amounts to encode data bits. These studies have no considerations on transmission and reception channels, which implies MAC (medium access control) protocols that control the channels.

III. Design of WiChest

A. Key Idea

Our key idea is to detect WiFi-AP signals in multiple ZigBee channels. Figure 2 shows WiFi and ZigBee channels. As shown in Fig. 2, a WiFi channel overlaps with four specific ZigBee channels. We can estimate a WiFi-AP operating channel based on ZigBee channels where the AP signals are detected. There are many WiFi APs in practical environments. We group WiFi-AP signals by sender APs and then estimate the channel of the each AP.

B. Design Overview

Figure 3 depicts an overview of WiChest, a WiFi-AP operating channel estimator. The WiChest consists of three blocks: a multi-channel AP detector, AP signal splitter, and channel estimator. The multi-channel AP detector detects APs in multiple ZigBee channels using a sensor node. For the each detected AP, the sensor node records AP information: ZigBee channel number where the AP is detected, AP-RSS (received signal strength), and beacon index that carries beacon timing information. The AP signal splitter analyzes the AP information to group the AP information by sender APs. The grouped AP information is then processed by the channel estimator to estimator an AP operating channel.

Following subsections present design details of the each block.

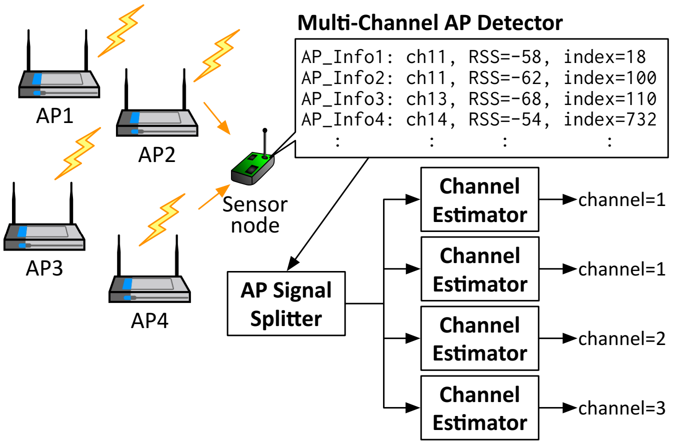

Fig. 3. Overview of WiChest

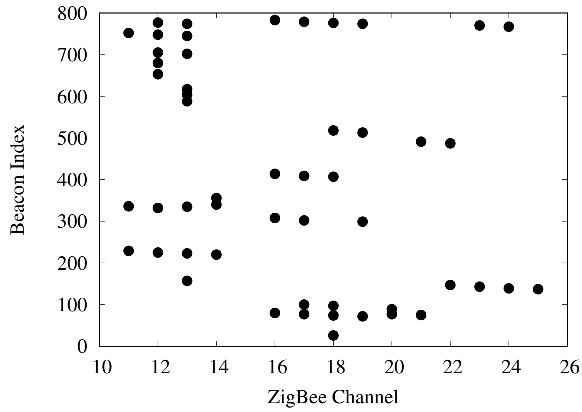

Fig. 5. Example of AP signals mapped in (*ZigBee channel*)–(*beacon index*) feature space

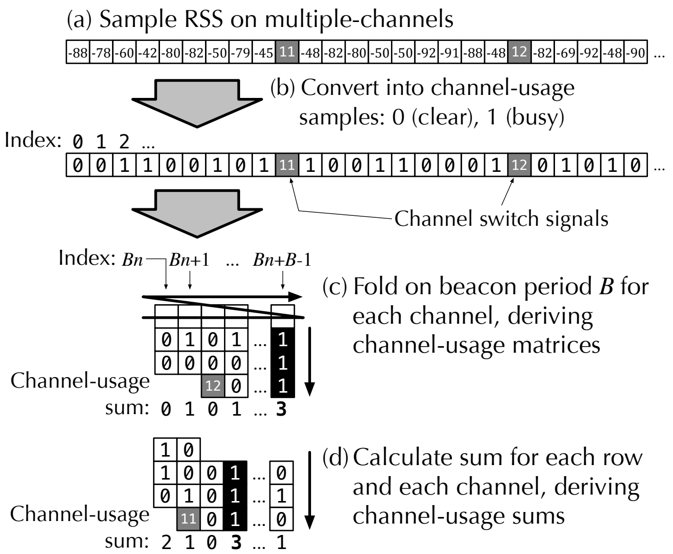

Fig. 4. Overview of multi-channel AP signal detection. a) A sensor node samples RSS and periodically switches its observation channel, and b) convert the RSS samples into channel-usage samples. c) The sensor node groups RSS samples by channels and folds the channel-usage samples on beacon period, deriving channel-usage matrices. For each channel-usage matrix, d) the sensor node calculates the sum for each column to get channel-usage sums. Periodic beacon signals appear in a column, which results in large channel-usage sum.

C. Multi-Channel AP Detector

Figure 4 depicts an overview of multi-channel AP detection. To detect AP signals on a sensor node, the sensor node periodically samples RSS. Note that all ZigBee (IEEE 802.15.4) modules have an RSS measurement function as an energy detection function defined in the standard [29]. The sensor node can detect WiFi signals because both WiFi and ZigBee are using the same 2.4-GHz band.

The sensor node changes its observation channel after a specific number of samples are collected. Channel switch takes some time to restart radio circuits. We embed channel switch signals instead of RSS samples during the channel switch period. Because ZigBee modules provide average RSS over 128 microseconds, which is defined in the standard, we set an RSS sampling period to 128 microseconds not to miss WiFi signals while minimizing the sampling rate.

The collected RSS samples are converted into channel-usage samples: `0` for clear and `1` for busy. We use a threshold of -77 dBm for channel-usage determination, which follows after the default threshold of a CC2420 IEEE 802.15.4 module for clear channel assessment [30].

The channel-usage samples are grouped by observation channels and are folded on the AP beacon period, resulting in channel-usage matrices. To preserve beacon timing information, a part of the each matrix might be missing, as shown in Fig. 4. We calculate the sum for each column in each channel-usage matrix. These sums are named *channel-usage sums*.

We can detect AP signals in each ZigBee channel by finding a column whose channel-usage sum is above a threshold. AP beacon signals whose interval matches to the folding period appear in a specific column. Large channel-usage sum therefore indicates that there are beacon signals whose interval matches to the folding period. Referring to our previous paper [2], we set the threshold of channel-usage sum to 80 % of the number of foldings.

AP-RSS is calculated by averaging RSS samples of the detected AP signal. RSS samples corresponding to the AP-signal columns in a channel-usage matrix are extracted and averaged. Note that we employ a simple edge filter to reduce the RSS measurement error [1].

In practical environments, we can observe multiple APs in a ZigBee channel. We utilize *beacon index* and recognize signals from an identical AP in an AP signal splitter. Beacon index is a column index number in a channel-usage matrix where AP signals are detected. Periodic AP beacon signals are observed in an identical column in a channel-usage matrix in different ZigBee channels. AP signals from an identical AP therefore have an identical beacon index.

D. AP Signal Splitter

The AP signal splitter applies a clustering method in a two-dimensional feature space, i.e., a (*ZigBee channel*)–(*beacon index*) space, to group AP information by sender APs. We don't limit the clustering method to apply. Clustering methods

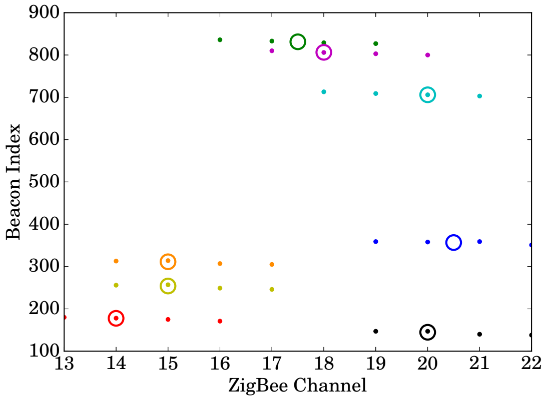

Fig. 6. Example of AP signal grouping using mean-shift clustering (scale factor $\gamma = 0.20$). Points are AP signals mapped in a feature space. Circles are centers of clusters in mean-shift and the color represents each group.

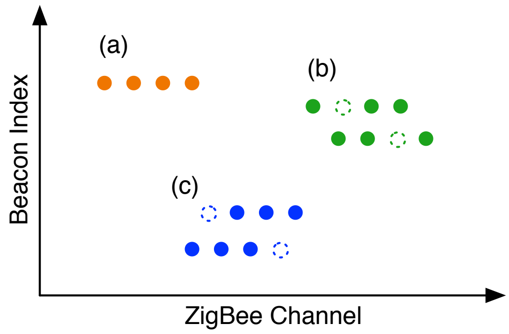

Fig. 7. Possible combinations of ZigBee channels where AP signals are detected. (a) Detected in four successive channels, (b) missing in a second or third channel, and (c) missing in a first or last channel.

that require no input of number of clusters are recommended because the number of APs around a sensor node is unknown.

Figure 5 shows an example of AP signals mapped in the feature space. Figure 5 shows 20 APs detected by the multi-channel AP detection scheme presented in the previous subsection. We can observe that signals from an identical AP are represented by four points in a row. Signals from an identical AP are detected in four successive ZigBee channels and have the same beacon index. Note that some APs are represented by less than four points because AP signals sometimes cannot be detected in some ZigBee channels due to noise and other WiFi device signals.

To ensure the effectiveness of our signal splitting scheme, we use *mean-shift* clustering as an example. Mean-shift does not require the number of clusters but requires a radius, or a bandwidth, for clustering. The radius is determined based on two considerations below:

- Signals from an AP can be observed in four successive ZigBee channels. The distance between signals from an identical AP is at most three in a ZigBee channel dimension.
- Beacon index is suffered from jitter due to an asynchronous operation of APs and sensor nodes. Crystal oscillators in WiFi and ZigBee modules have a frequency deviation of approximately ± 100 ppm. A multi-channel AP detection requires approximately three seconds for sampling RSS in each ZigBee channel [2]. The frequency deviation therefore results in jitter of ± 1.2 milliseconds, which equals to ± 9.4 RSS-sample length, for a four-channel observation.

The required radius is different in ZigBee channel and beacon index dimensions. We therefore scale the feature space in a beacon index dimension with a scale factor γ and use a radius of 3.0.

Figure 6 shows a successful example of AP signal grouping using mean-shift clustering with the scale factor $\gamma = 0.20$. AP signals were detected in the environment where eight WiFi APs were available. Points in the figure are AP signals. Circles are cluster centers and the color represents each group. Although two APs have almost same beacon index around 830, the AP signals successfully grouped into two APs.

E. Channel Estimator

The channel estimator estimates WiFi-AP operating channels based on ZigBee channels where AP signals are detected. AP signals could be detected in four successive ZigBee channels. In practical environments, however, sensor nodes might not detect AP signals in some channels due to noise and other WiFi signals. We designed a simple channel estimation algorithm that can be used when AP signals are detected in three or four ZigBee channels.

Figure 7 depicts possible combinations of the three or four ZigBee channels where AP signals are detected. AP signals are mostly detected in (a) four successive channels. But AP signals are sometimes missing (b) in a second or third channel, or (c) in a first or last channel.

The channel estimator checks if the ZigBee channels where AP signals are detected are four successive channels. Using the four successive channel numbers, we can easily estimate the AP operating channel referring to Fig. 2. If AP signals are detected in three ZigBee channels, the channel estimator determines a channel where AP signals are missing. The estimator then virtually detects AP signals in the missing channel to estimate the AP channel. Let c_s, c_s+1, c_s+2, and c_s+3 are the channels where AP signals are really or virtually detected. WiFi-AP operating channel $\widetilde{c_w}$ can be estimated as

$$\widetilde{c_w} = c_s - 10. \tag{1}$$

IV. Evaluation

To evaluate channel estimation accuracy of WiChest, we conducted experimental evaluations in our laboratory using an actual sensor node and WiFi APs.

A. Experiment Setup

Figure 8 shows an experiment setup. We used WNDR4300 WiFi APs from Netgear running OpenWrt and a MICAz sensor node from Crossbow that employs a CC2420 IEEE 802.15.4 module. A data processing laptop was MacBook Pro running

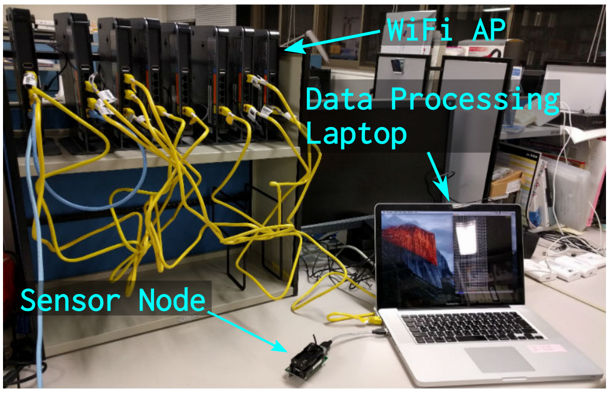

Fig. 8. Experiment setup

Mac OSX 10.11. WiChest channel estimation process was implemented as a Python program running on the data processing laptop.

The sensor node and eight WiFi APs were installed on a desk separated by approximately one meter. The sensor node certainly detects the AP signals in such short distance. The channels of the APs were randomly chosen from 1 to 11. The sensor node periodically switched its ZigBee channel from 11 to 26 while sampling RSS (received signal strength) in each channel. The RSS samples were collected for four seconds in each ZigBee channel. The length of RSS samples is determined based on memory limitation on a MICAz sensor node. There were 20 WiFi APs other than our eight APs in our laboratory. Beacon intervals of the eight APs were configured to 109 TU to safely distinguish the eight APs from other APs. Scale factor γ of beacon index, which is presented in Section III-D, was changed from 0.05 to 0.5. We repeated the channel estimation for 500 trials.

We compared the estimated channel numbers with actual channel numbers of the APs and evaluated the numbers of true positives (TPs), false negatives (FNs), false positives (FPs), and true negatives (TNs). TP, FN, FP, and TN are defined as the case that an AP channel was correctly estimated, no AP was detected in a channel where AP was available, an AP was detected in a channel where no AP was available, and no AP was detected in a channel where no AP was available, respectively. The number of unused channels in each trial was used to evaluate TNs.

Using the numbers of TPs, FNs, FPs, and TNs, we calculated accuracy, precision, recall, and F-measure defined as:

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN} + \mathrm{TN}}, \tag{2}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \tag{3}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \tag{4}$$

$$\mathrm{F_{measure}} = \frac{2 \cdot \mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}. \tag{5}$$

B. Experiment Result

Figure 9 shows the number of true positives (TPs), false negatives (FNs), false positives (FPs), and true negatives (TNs) as a function of a scale factor γ of beacon index. Figure 9 indicates the following:

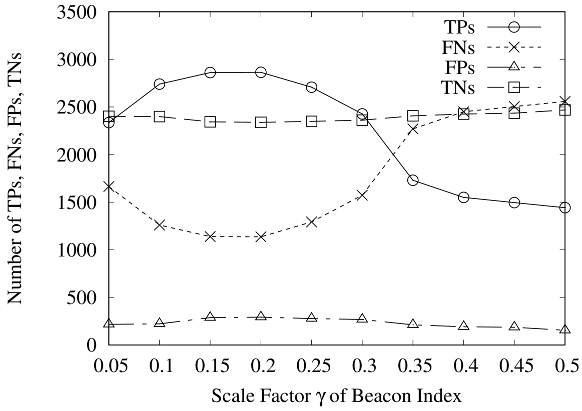

Fig. 9. Numbers of true positives (TPs), false negatives (FNs), false positives (FPs), and true negatives (TNs) as a function of scale factor γ of beacon index

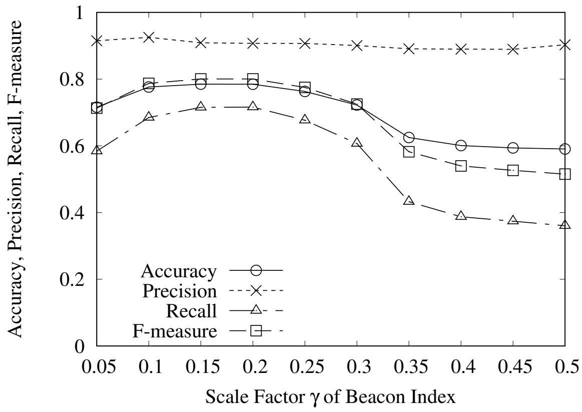

Fig. 10. Accuracy, precision, recall, and F-measure as a function of scale factor γ of beacon index

1) Increase in the scale factor γ increased the number of TPs when $\gamma < 0.20$ and the number of TPs became maximum at $\gamma = 0.20$. When $\gamma > 0.20$, increase in γ resulted in decrease in the number of TPs. The scale factor γ defines allowable separation in a beacon index dimension in an AP signal grouping. The scale factor $\gamma = 0.20$ is equivalent to a mean-shift radius of 15 in a beacon index dimension. Jitter due to an asynchronous operation of a sensor node and APs was almost same as we expected in Section III-D.
2) The numbers of TPs and FNs were symmetric about a line parallel to the x-axis. The sum of the numbers of TPs and FNs was constant at 4,000 because we used eight APs and repeated experiment for 500 trials.
3) The numbers of FPs and TNs were almost independent of the scale factor γ. The scale factor γ relates to the performance of AP signal grouping. We can guess that FPs and TNs mainly occurred in AP signal detection and AP channel estimation.

We next calculated accuracy, precision, recall, and F-measure. Figure 10 shows accuracy, precision, recall, and F-measure as a function of the scale factor γ. Figure 10 indicates the following:

1) Accuracy, recall, and F-measure exhibited similar curves as a function of the scale factor γ. These curves are also similar to a TP curve in Fig. 9. The numbers of FPs and TNs were almost constant as γ varies. The numbers of TPs and FNs were dominant factors in variations of accuracy, recall, and F-measure.
2) Accuracy, recall, and F-measure were maximum at the scale factor $\gamma = 0.20$. The maximum values of accuracy, recall, and F-measure were 0.78, 0.72, and 0.80, respectively. Accuracy, precision, recall, and F-measure were almost constant near the maximum point. We can easily adjust the scale factor γ to get the near-maximum performance.
3) Precision was almost independent of the scale factor γ. This is because the number of FPs was small compared to the number of TPs. The average precision was 0.90.

The above results confirm that the WiChest accurately estimated AP operating channels with an F-measure of 0.80.

V. Conclusion

This paper presents WiChest, a WiFi-AP channel estimator working on sensor nodes. WiChest is based on an observation that WiFi signals are detected in four successive ZigBee channels. A sensor node detects AP signals in multiple channels using a cross-technology signal extraction scheme. The AP signals are then grouped by sender APs using mean-shift clustering. Checking channel numbers where the AP signals are detected, we can easily estimate AP operating channels. We implemented WiChest using a MICAz sensor node and evaluated the basic performance using actual WiFi APs. Experimental evaluations demonstrated that WiChest accurately estimated AP channels with an F-measure of 0.80.

Acknowledgment

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