# Impact of Surrounding Information on Wi-Fi Sensing Efficiency

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***Abstract*—One of essential parts of mobile applications using Wi-Fi is an energy-efficient Wi-Fi sensing. Lately, there have been many studies on Wi-Fi sensing algorithms using surrounding informations (*e.g.*, bluetooth ID [1], cell ID [2] and speed [3], etc). Based on the correlation between such informations and Wi-Fi encounters, the algorithms can determine the wake-up time from sleep mode to detect a Wi-Fi AP efficiently. In this paper, we measure and compare the impact of each surrounding information on the Wi-Fi sensing efficiency by analyzing the uncertainty of information-conditioned *remaining time* of a mobile until its next Wi-Fi encounter. Using three metrics (*i.e.*, information gain, conditional expectation and variance) on a real mobility trace, we measure to what extend each surrounding information can reduce the uncertainty of the remaining time, which turns out to be the improvement of Wi-Fi sensing efficiency. Comparing such gains from all surrounding informations, we show that the cell ID information is more energy-efficient than bluetooth ID, speed and even all possible combinations of them in Wi-Fi sensing.**

## I. Introduction

A number of smartphone and tablet users start to generate much heavier mobile traffic from their mobile applications [4]. This mobile data explosion is expected to be a major obstacle to the success of the mobile communication service business. Upgrading to 4G is clearly one solution, yet mobile network operators are still seeking for many other low-cost alternatives to diversify the solution options.

Another solution of mobile data explosion is offloading cellular data to Wi-Fi access points (APs)[1] which have much higher bandwidth and lower price than 3G. Recently, many studies have shown that the Wi-Fi offloading is highly promising. Lee *et al.* [5] showed that about 70% of cellular data can be offloaded to Wi-Fi if users can tolerate an hour delay. In practice, several delay-tolerant applications over Wi-Fi are deployed and popularly used, *e.g.*, iCloud [6] and Microsoft Pocket Outlook [7], which show the possibility of Wi-Fi offloading. At above applications, mobile data traffic is not served until encountering an AP and when a mobile device contacts with an AP spontaneously, the data is delivered through the AP. However, to fully utilize Wi-Fi APs in users' vicinity when they move, a smartphone is required to consume additional energy for AP scanning in the background process, which is one of users' biggest concerns [1]–[3], [8], [9]. In fact, current smartphones turn on and scan an AP on demand [3] to save energy. However, this on-demand method losses vast amount of WiFi contacts [3].

Many algorithms for energy-efficient Wi-Fi sensing exploit surrounding informations (*e.g.*, cell ID [2], a bluetooth contact list [1] and speed [3]), which are intrinsically available (*e.g.*, cell ID) or easily measurable (*e.g.*, speed, bluetooth) on a mobile device, when they predict AP contacts and determine sleep period. The basic intuition behind them is that the correlation between AP contacts and surrounding information is useful in predicting the current or future AP contacts. However, those algorithms essentially require additional energy for gathering surrounding informations [1] as well as the computing resource for matching patterns of gathered information to the history data. Consequently, they may incur additional overheads which may be crucial for battery-equipped smartphones. Hence, it is important for a Wi-Fi sensing algorithm to pick the most efficient surrounding information. To the best of our knowledge, it is still unclear that (i) which surrounding information is more useful than others and (ii) how much surrounding information can increase the Wi-Fi prediction accuracy. In this paper, we provide an analytical framework to understand and compare the impact of three popular surrounding information (*3G cell*, *speed* and *bluetooth* information) and their combinations on the sensing efficiency, which in turn provides the engineering insight on the design of an efficient Wi-Fi sensing algorithm.

One of the most important metrics in AP sensing is the *remaining time* until encountering an AP, which we focus on this paper[2]. Based on the distribution of a remaining time conditioned by the given surrounding information, a sensing algorithm is able to determine Wi-Fi sleep periods until next sensing to optimize its objective.[3] If the uncertainty of a remaining time is pretty high, those algorithms may consume huge energy with consecutive AP detection failures or miss several APs in vicinity. We study the impact of each surrounding information on Wi-Fi sensing metric (*i.e.*, remaining time), using 1 year traces of 38 participants distributed in Nokia mobile data challenge (MDC) competition [10]. Based on three analysis techniques, we quantify to what extent each surrounding information (*i.e.*, cell ID, bluetooth, speed and combinations of multiple information) can reduce the uncertainty in estimating remaining time. Comparing them, we finally conclude that using only cell ID in the AP sensing is most efficient among all

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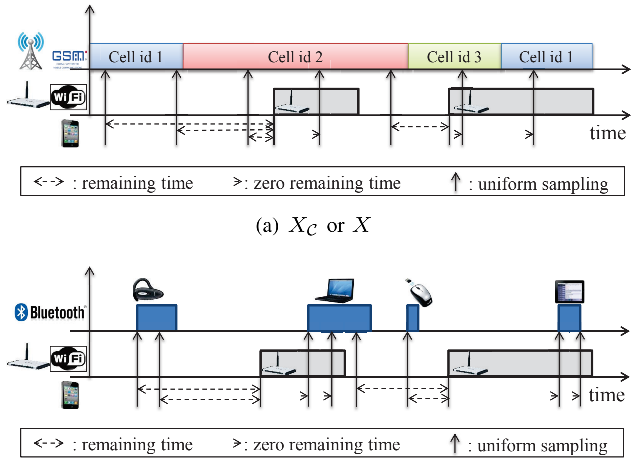
[1]We simply use 'AP' instead of 'Wi-Fi AP', unless confusion arises.

[2]we regard remaining time as a random variable

[3]We call this family of algorithms as a canonical form of sensing algorithms.




(a) $X_{\mathcal{C}}$ or $X$

(b) $X_{\mathcal{B}}$

Fig. 1. the illustration of the definition of remaining time $X$ and $X_{\mathcal{B}}$.

possible candidates which include even the combination of cell ID and bluetooth ID. To the best of our knowledge, it is the first work that provides a theoretical framework to compare the impact of each surrounding information on a Wi-Fi sensing.

## II. Related Work

There are two ways of sensing Wi-Fi APs: (i) The first one is to stay in Wi-Fi idle-listening mode where the mobile can detect the beacon packets from APs in a vicinity [11], [12], and (ii) the second is to repeatedly "sleep and scan" with Wi-Fi sleep mode [13]. Comparing the above two schemes, [12] shows that "sleep and scan" consumes much less energy than using "idle-listening mode", since the energy consumption in Wi-Fi sleep mode is negligible. However, "idle-listening mode" can immediately detect APs as soon as it enters the coverage of the AP, whereas "sleep and scan" may experience the detection delay due to the sleep interval.

Many of previous researches have studied on the efficient "sleep and scan", exploiting the correlation between AP contacts and surrounding information. WiFisense [3] uses accelerometer information to sense a user's movement which improves the Wi-Fi contact estimation. Cellular footprint [1], [2] utilizes the currently associated cell tower to estimate the on/off state of Wi-Fi contact. In addition, Bluefi [1] exploits the logs of bluetooth contacts which can be measured with ten times less energy than scanning APs. In [1], users maintain the list of bluetooth devices which are located in AP coverage, and when a bluetooth device in the list is detected, the mobile turns on Wi-Fi from the sleep mode and scans APs. In this paper, among those candidates of surrounding information, we quantify which information is most efficient in Wi-Fi sensing algorithm. To the best of our knowledge, this is the first work to compare the impact of each surrounding information.

## III. Model and Sensing metrics

### A. Models

***Wi-Fi AP on/off process.*** We assume that the average throughput of all APs are the same so that we regard a number of available APs as a unique AP. Wi-Fi APs are deployed over many hot-spots as well as other human-visiting places (*e.g.*, office, home and campus). However, due to the small coverage of APs and users' mobility, each mobile frequently moves in and out of Wi-Fi AP coverage, which in turn generates Wi-Fi AP on/off processes experienced by mobile users.

***Wi-Fi Sensing.*** Each mobile is occasionally sensing Wi-Fi APs or turned off (*i.e.*, Wi-Fi sleep mode) to save energy. We assume that if data traffic is arrived at a Wi-Fi transmission queue [5]–[7], a sensing algorithm computes the length of sleep period based on the the average remaining time which will be described later and turns it into a sleep-mode. Then, after the sleep period, it wakes up and scans AP beacon signals. It is well known that Wi-Fi sensing consumes considerable amount of energy [3]. If the device is not under AP coverage, it fails to detect an AP and sets a new sleep period.

***Surrounding information.*** During the above sensing procedure, each smartphone can measure its surrounding informations (*e.g.*, cell ID, bluetooth ID and accelerometer). We assume that bluetooth and accelerometer are implemented on every smartphone and known to the Wi-Fi sensing module. Using them, a smartphone can exploit three surrounding informations (*i.e.*, GSM cell ID, bluetooth and speed) on the energy-efficient sensing. For cell ID information, we denote $\mathcal{C}$ as a set of GSM cell IDs and $C \in \mathcal{C}$ as a GSM cell ID. In a similar way, we denote $\mathcal{B}$ as a set of bluetooth IDs[4] and $\mathcal{S}$ as a set of user speed range (*e.g.*, slow, medium and fast). $B \in \mathcal{B}$ is the condition of bluetooth ID and $S \in \mathcal{S}$ is a user speed range. We call an element in sets $\mathcal{C}, \mathcal{B}$ and $\mathcal{S}$ as an *event.*

### B. Canonical form of Wi-Fi sensing algorithm

Throughout this paper, we consider a canonical form of Wi-Fi sensing algorithms commonly used in Wi-Fi networks [1]–[3]. It works as follows. 1) When the upload request is arrived [5]–[7], the mobile first measures current surrounding information such as cell ID, bluetooth MAC address and speed. 2) Exploiting the correlation between each surrounding information and previous Wi-Fi contacts in history data, the mobile estimates the *remaining time* until the next Wi-Fi AP contact as well as its randomness (distribution). 3) Based on the estimation of the remaining time, the mobile sets the best sleep period with respect to the energy-efficient sensing and goes into the Wi-Fi sleep mode. Note that computing the best sleep period depends on the objective and intelligence of algorithms, which is not our focus. 4) When a mobile wakes up and fails to detect an AP, it repeats the procedure from '2)'.

### C. Remaining time

We consider a scenario where packet transmission requests over Wi-Fi from delay-tolerant applications are uniformly distributed over entire time span. In this case, the randomness (or uncertainty) of the remaining time from a random request arrival to the encountering an AP is directly related to the efficiency of sensing algorithms. For instance, if an algorithm sets its sleep period as the expected remaining time, the error in estimating the sleep period due to high uncertainty

[4]Since multiple bluetooth devices can be encountered at a same time, we regard a list of bluetooth IDs in the vicinity as a condition $B$.

of the remaining time may incur consecutive sensing failures with huge energy consumption. In another example where an algorithm aims at minimizing loss of Wi-Fi contact opportunity and the uncertainty of the remaining time is still high, the algorithm tries to scan APs densely over time spending a lot of sensing energy, since candidate values of future remaining times tend to be widely and uniformly distributed under high uncertainty. However, the lower uncertainty of remaining time enables us to estimate more correct sleep period, which in turn facilitates more efficient Wi-Fi sensing.

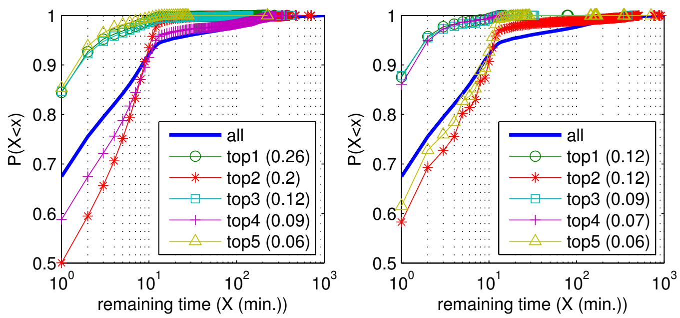
We denote $X$ as a random variable of remaining time from a uniformly sampled time to the next AP encounter in a Wi-Fi AP on/off process. In addition, we define another type of remaining time whose start time is uniformly sampled only when a surrounding information is measured. This is because, some surrounding information such as bluetooth ID may not be always available on smartphones. We denote such remaining time as $X_{\mathcal{A}}$ where $\mathcal{A}$ is the set of the corresponding surrounding information. Fig. 1 illustrates how to measure the remaining time $X$, $X_{\mathcal{C}}$ and $X_{\mathcal{B}}$ in a Wi-Fi on/off process. In Fig. 1(a), $X_{\mathcal{C}}$s are measured from a user's Wi-Fi on/off process and its associated cell id sequence. Since cell id can be always available in each smartphone, $X_{\mathcal{C}}$ is the same as $X$. Note that when a mobile is under AP coverage, the sampled remaining time is zero. In case of using bluetooth information, smartphones do not always encounter the bluetooth devices but sparsely encounter them due to small coverage of bluetooth radio range. Hence, when we analyze the remaining time on condition that there is at least one neighboring bluetooth device, *i.e.*, $X_{\mathcal{B}}$ from a real trace, we do not sample them uniformly over entire time span but only when bluetooth devices are measured as illustrated in Fig. 1(b).

## IV. Analysis techniques

Comparing the impact of all surrounding informations is rather challenging, since the contribution to a sensing efficiency is not well-defined. To tackle this problem, we introduce three notions - *Information gain, Conditional bias* and *Conditional normalize variance* - that quantify the contribution of a surrounding information.

### A. Information gain

*Information gain* [14] is based on the concept of entropy. Entropy is a measure of the uncertainty associated with a random variable. The entropy of random variable $X$ is defined as $H(X) = \sum_i P[X = x_i] \log \frac{1}{P[X=x_i]}$, where $P[X = x_i]$ is the probability that $X = x_i$. In case where $X$ is a continuous variable (*e.g.*, remaining time), $X$ should be discretized to $X'$ and compute $H(X) = \sum_i P[X' = x_i] \log \frac{1}{P[X'=x_i]}$. In our analysis, we divide the states of remaining time by 5 minutes, *i.e.*, $X' \in \{0, 5\text{mins}, 10\text{mins}, \ldots\}$, and we regard $X' = 5\text{mins}$ if $5\text{mins} \leq X < 10\text{mins}$. The conditional entropy of $X$ given another random variable $Y$ is $H(X|Y) = \sum_j P[Y = y_j] H(X|Y = y_j)$, where $Y$ is a random variable of a surrounding information. The information gain is $H(X) - H(X|Y)$ and the relative information gain is $\frac{H(X)-H(X|Y)}{H(X)}$.




(a) Cell ID (b) Bluetooth ID

Fig. 2. CDF of remaining times conditioned by 5 top IDs for a participant (user index is 4) in (a) cell and (b) bluetooth informations. The thick blue lines in both (a) and (b) indicate CDFs of all remaining times. The number in the bracket for each legend represents the fraction of contacts over the total experiment time.

This metric indicates the amount of uncertainty reduction in $X$ from our knowledge (surrounding information) $Y$.

### B. Expectation and Variance

We further develop two notions based on conditional expectation and variance of $X$. Since entropy is measured by splitting continuous random variable $X$ into discrete states, it cannot capture the amount of time error in estimating $X$ (*i.e.*, $X - \mathbb{E}[X]$).

***Conditional bias.*** We define the conditional bias in expectation as $\sum_j P[Y = y_j] \left| \mathbb{E}[X|Y = y_j] - \mathbb{E}[X] \right|$. This measure shows how much the estimated value conditioned on an event $y_j$, $\mathbb{E}[X|Y = y_j]$ is deviated from the expectation of $X$. If the deviation from the expectation is large, the surrounding information is significant in predicting the remaining time.

***Normalized conditional variance.*** The normalized conditional variance is defined as $\sum_j P[Y = y_j] Var(X|Y = y_j)/Var(X)$. Variance not only represents the uncertainty in estimating the remaining time, as in entropy, but also captures the value of $X$. The decrement in variance can be interpreted as the reduced estimation error by conditioning the surrounding information. In particular, if the variance $Var(X|Y = y_j)$ gets smaller by a condition $y_j$, the condition can significantly improve the accuracy of remaining time estimation as well as the efficiency of a Wi-Fi sensing algorithm.

## V. Metric Analysis: Single Information

We use mobile traces of 38 participants distributed by Nokia in Mobile Data Challenge (MDC) [10]. The traces contain WiFi contact and surrounding informations such as cell ID, bluetooth ID and accelerometer experienced by participants for about one year. Using three analysis techniques in Section IV, we evaluate the impact of surrounding informations on the remaining time as well as the Wi-Fi sensing efficiency. Based on those evaluations, we compare the contribution of each surrounding information.

### A. Remaining time on each condition

***Conditional distribution.*** We depict the cumulative distribution function (CDF) of remaining times for a randomly selected participant (the user index is 4 in other figures.) in Fig. 2. In

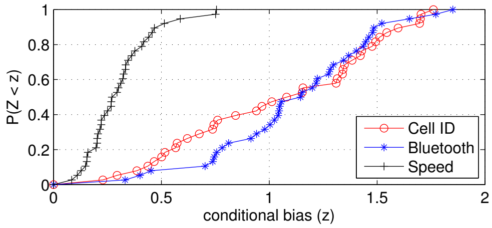



Fig. 3. Conditional biases of 38 participants.

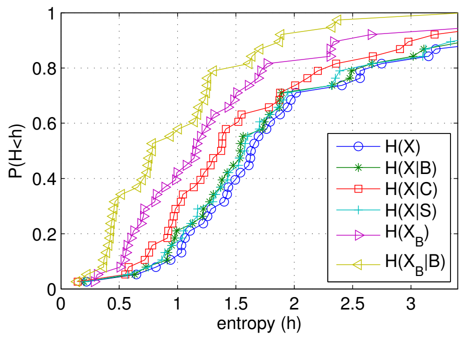



Fig. 4. CDF of entropies of 38 participants.

Figures 2(a) and (b), we depict remaining times conditioned by encountered cell ID and bluetooth ID, respectively. Since each participant encountered a lot of cells and bluetooth devices, we pick the top five IDs sorted by the fraction of the contacts over the total experiment time. In Fig. 2(a), the cell of *top1* (green line) is conjectured to be a hot-spot area where Wi-Fi APs are densely deployed, since the remaining time in this area is lower than that in others.

Similarly, in Fig. 2(b), the bluetooth device of *top1* (green line) may be located close to a Wi-Fi AP. From both cases, we observe that the conditional distributions of remaining times are quite different from each other.

***Conditional bias.*** To measure the difference of each conditional distribution, we compute the conditional bias in terms of expectation as we defined in Section IV. Fig. 3 shows the CDF of conditional biases measured from all participants. For 50% of participants, the expectations conditioned by both cell and bluetooth IDs are biased more than 110% against $\mathbb{E}[X]$, while speed shows only 30% bias. Thus, we address that both cell and bluetooth informations are crucial in predicting a remaining time while speed information is less important than cell and bluetooth IDs. If we use the surrounding information in estimating the remaining time, a scanning algorithm would yield the biased sleep time according to given condition (*e.g.*, shorter sleep time in *top1* cell ID and longer sleep time in *top2* cell ID in Fig. 2(a)), which is more accurate than $\mathbb{E}[X]$. Comparing conditional biases from cell and bluetooth informations, we observe that the cell information deviates the expectation slightly more than bluetooth. Yet, the conditional bias does not represent how precisely we can estimate remaining time based on surrounding information, because it does not contain the second moment of the distribution, such as variance.

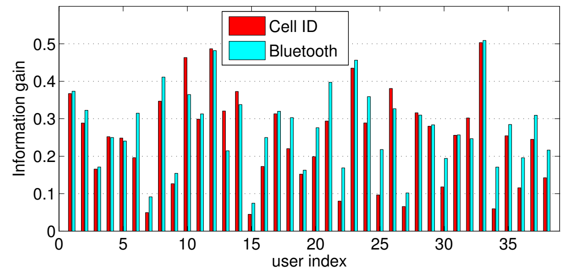


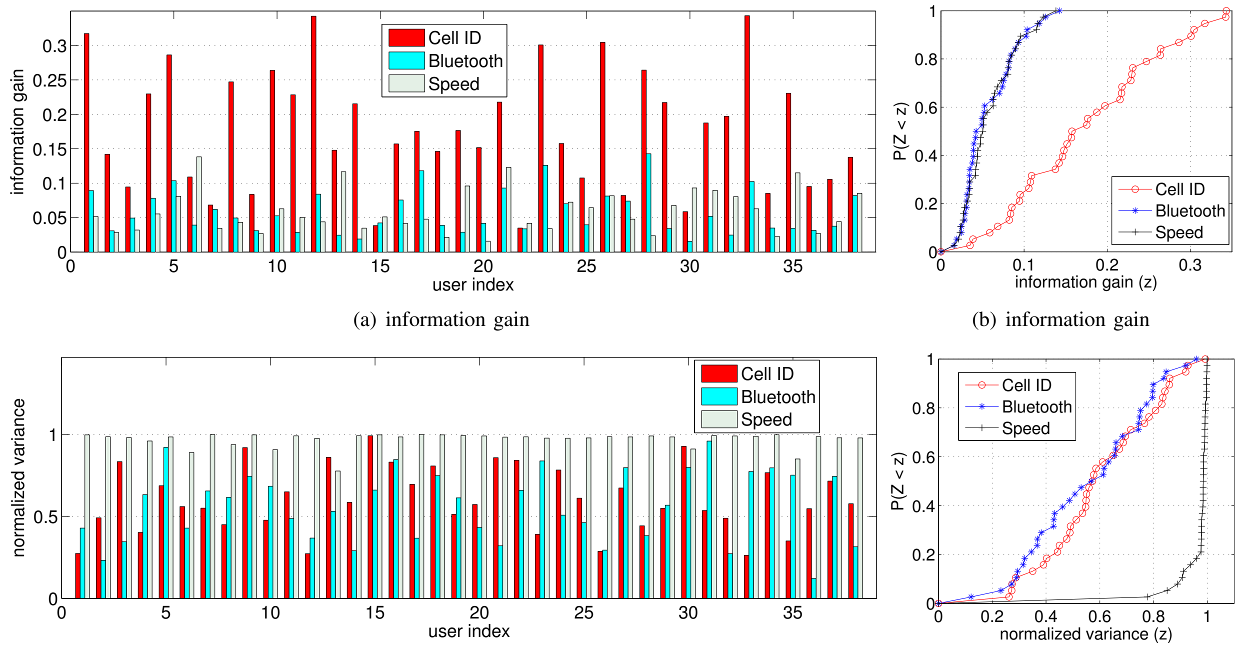

Fig. 6. Information gain of bluetooth IDs on $X_{\mathcal{B}}$.

### *B. Information gain of surrounding elements*

Now, we analyze the uncertainty of remaining time which is closely related to the efficiency of a Wi-Fi scanning algorithm. ***Entropy.*** Figure 4 plots the distribution of conditional entropy of remaining time for 38 participants. Recall that $X_{\mathcal{B}}$ is a remaining time where a smartphone encounters at least one bluetooth device. Comparing the entropy of $X$ with $X_{\mathcal{B}}$, the uncertainty of a remaining time with a bluetoothe device is much smaller than the uncertainty of $X$ which is measured over entire time span. In other words, the existence of a neighboring bluetooth device irrespective of its ID is still closely related to the AP contacts. For example, if we visit an office where Wi-Fi APs are located, there may exist bluetooth mouses, keyboards or headsets which can be measured by smartphones. In the following section, we will analyze the uncertainty reduction when we know IDs of each surrounding information.

***The impact on $X$.*** Figures 5(a) and (b) show the information gain of cell, bluetooth IDs and speed range on $X$. In the set of bluetooth events, $X_{\mathcal{B}}$ which corresponds to encountered bluetooth IDs, we add the bluetooth-off event to fairly compare the impact on $X$ with cell IDs. Information gains from cell IDs are shown to be larger than that from bluetooth IDs for most of participants. The average information gain of cell ID, bluetooth ID and speed range is 17%, 6% and 7%, respectively. The small information gain of speed range can be easily followed by the result of its conditional bias in Section V-A, which shows much lower deviation than cell and bluetooth IDs. The reason behind the huge difference between cell and bluetooth IDs is that the opportunity of meeting surrounding bluetooth devices occurs sparsely, whereas the cell information is always available. In fact, the fraction of time that at least one bluetooth device is recorded over the total experiment time is 29% on average. From this result, we conclude that the cell ID information is much more effective in Wi-Fi sensing than bluetooth and speed.

***The impact of cell and bluetooth IDs on $X_{\mathcal{B}}$.*** Now, we focus on the remaining times where there exists at least one bluetooth device in the vicinity. We have already shown that $X_{\mathcal{B}}$ has less uncertainty than $X$ in Fig. 4. In addition, in Fig. 6, the average information gains of cell and bluetooth IDs are 24% and 27% respectively, which shows that both cell and bluetooth IDs provide significant information gains on $X_{\mathcal{B}}$. In other words, using cell and bluetooth IDs rather than using only bluetooth on-off events can reduce a huge amount of uncertainty in Wi-Fi contact estimation. Due to the difference between the radio ranges of bluetooth and cellular signals, cell information provides coarse-grained location information, while bluetooth




(a) information gain (b) information gain

(c) normalized conditional variance (d) normalized conditional variance

Fig. 5. Single information case : (a) the information gain for each participant (b) CDF of information gains (c) the normalized conditional variance for each participant (d) CDF of normalized conditional variance.

information provides fine-grained location information. Hence, we observe that information gain of bluetooth on $X_{\mathcal{B}}$ is slightly higher than cell ID for most participants. From this result, we conclude that the information gain of bluetooth IDs on $X$ is low because the bluetooth information is sparse, and the information gain of bluetooth IDs on $X_{\mathcal{B}}$ is significant.

### *C. Normalized conditional variance*

So far, we have discussed on the uncertainty of remaining time when each surrounding information is exploited. The information gain, however, does not provide how much the estimation error is, since entropy is based on discretized and independent states. Recall that remaining time is divided into discrete and independent states whose sizes are 5 minutes in computing information gain. Thus, we further study the normalized conditional variance for each surrounding information.

Figures 5(c) and (d) show the normalized conditional variances for all participants. Note that we consider only the events of bluetooth IDs, rather than including the bluetooth off event when conditioning bluetooth information. In Figure 5(c), the normalized variances for all participants are 0.6, 0.55 and 0.92 on average for cell ID, bluetooth and speed respectively. Most participants' variances conditioned by speed are larger than that of cell IDs and bluetooth IDs. This implies that the estimation error based on bluetooth ID and cell ID can be much smaller than that of speed. The variances of bluetooth ID is smaller than that of cell ID, because the relatively small radio range of bluetooth devices may provide more fine-grained location information than cell IDs.

## VI. Metric Analysis : Multiple information

In this section, we further consider the combination of surrounding informations, *i.e.*, cell ID-bluetooth, cell ID-speed, bluetooth-speed, since they are jointly available in smartphones.

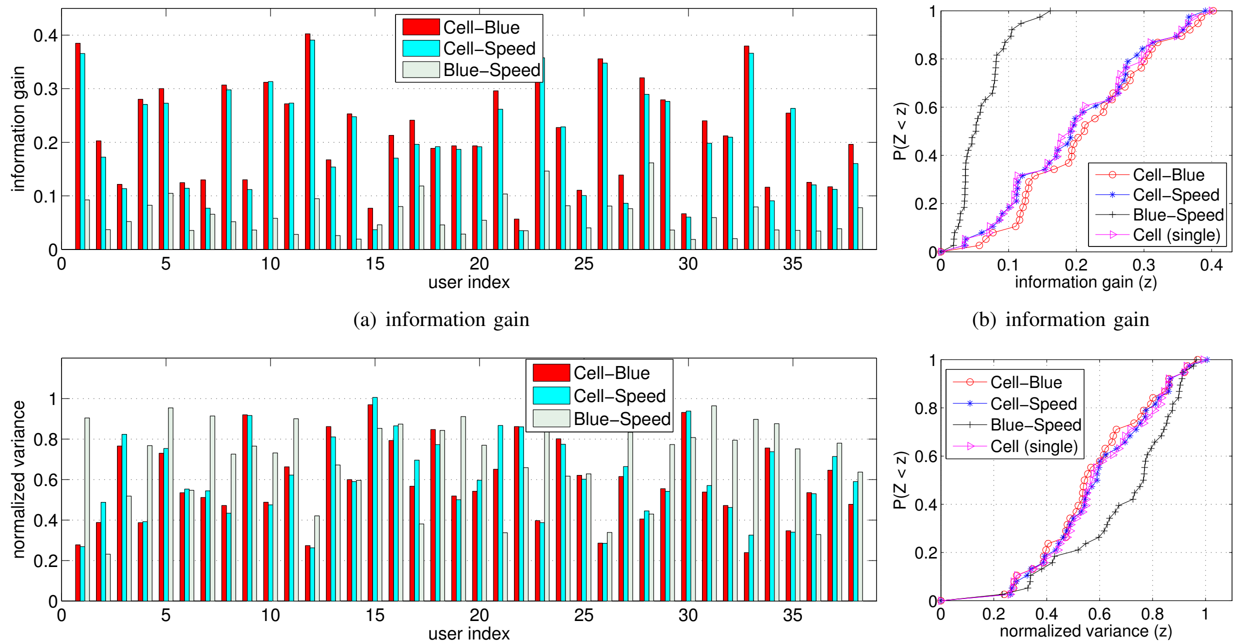
### *A. Information gain of multiple elements*

We test three combinations (*i.e.*, cell ID-bluetooth, cell ID-speed and bluetooth-speed). When an algorithm considers the combination of cell ID and bluetooth, the mobile maintains the statistics of remaining time conditioned by both cell ID and bluetooth in a training period.

Figure 7(a) shows the information gain of three combinations of surrounding information on $X$. The average information gain of 'cell-blue,'cell-speed' and 'blue-speed' are 22%, 20% and 6.2%, respectively. We first find that the gains of 'cell-blue' and 'cell-speed' are much higher than that of 'blue-speed' combination for most users As cell ID information shows the highest gain in single information case, the combinations containing cell ID performs much better than other combination. In Figure 7(b), we plot CDFs of information gains for all combinations and single information with cell ID. The information gain of cell ID is observed to be comparable to those of all possible combinations, which means that the cell ID is the dominant factor of information gain. Comparing the information gain between 'cell-blue' and 'cell-speed', we also observe that adding bluetooth to cell ID provides 1.6% higher average gain than adding speed or using cell ID itself. However, such a small benefit may not be sufficient to compensate the additional overhead from bluetooth information (*e.g.*, energy consumption for measuring the bluetooth devices [1]), for a energy-hungry device.

### *B. Normalized conditional variance*

Figure 7(c) plots the normalized conditional variance for all participants, whose averages are 0.58, 0.6 and 0.7 for 'cell-blue', 'cell-speed' and 'blue-speed', respectively. Similar to




(a) information gain

(b) information gain

(c) normalized conditional variance

(d) normalized conditional variance

Fig. 7. Multiple information case : (a) the information gain for each participant (b) CDF of information gains (c) the normalized conditional variance for each participant (d) CDF of normalized conditional variance.

the results in information gain, the normalized variances of 'cell-blue', 'cell-speed' and cell ID are almost the same, while 'blue-speed' shows higher variance. This again proves that the benefit from multiple surrounding informations is insufficient. To sum up, we conclude that using cell ID only is the most efficient way in Wi-Fi sensing and adding bluetooth and speed with the additional overheads (*e.g.*, energy consumption [1] and processing overhead) gives a small benefit.

## VII. Conclusion

In this paper, we quantify the effectiveness of each surrounding information (*i.e.*, cell ID, bluetooth ID and speed) on Wi-Fi sensing efficiency using three analysis techniques (*i.e.*, *conditional bias*, *information gain*, and *normailized variance*). We further investigate the impact of multiple informations in Wi-Fi sensing and compare them in terms of the uncertainty reduction in remaining time. Even though the combination 'cell-blue' shows the highest information gain in Wi-Fi sensing, we conclude that, for most of users, using only cell information is more efficient than using speed, bluetooth and other combinations. This is because, (i) bluetooth information is sparsely available compared to cell information, (ii) users' speed ranges are not closely correlated to Wi-Fi contact events, (iii) using multiple information does not provide sufficient gain to compensate for the additional overheads.

Our analysis result is based only on the Nokia trace where their Wi-Fi and bluetooth contact patterns can be biased. Thus, our conclusion could be modified in the future when bluetooth devices become more prevalent and Wi-Fi APs are densely deployed. However, we believe that our findings are widely applicable to the current wireless environment and our analysis can provide a new engineering insights on the design of advanced Wi-Fi sensing algorithms.

## Acknowledgment

This research was funded by the MSIP(Ministry of Science, ICT & Future Planning), Korea in the ICT R&D Program 2013

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