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I've heard you have problems: Cellular signal monitoring through UE participatory sensing

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***Abstract*— The operating environment of cellular networks can be in a constant state of change. One Singaporean operator expressed difficulty with the *coverage assertion* (*CA*) problem of whether regulated minimum coverage is met, especially in urban areas. Currently, the operator manually appraises coverage through laborious and expensive walk/drive-tests.**

In this paper, we propose *Tattle*, a distributed, low-cost and comprehensive cellular network measurement collection and processing framework. We exemplify Tattle by leveraging on participating UEs to report on network coverage in real-time.

Tattle exploits wireless local-area interfaces to exchange RSCP measurements amongst devices to preserve the co-locality of readings and conserve power. We propose U-CURE, a clustering algorithm which considers sample location uncertainty and the knowledge of device co-location to remove erroneously localized readings. We develop a prototype app on the Android™ platform as a proof-of-concept of the Tattle framework. We then use the Tattle framework to perform extensive RSCP measurement collection and processing in various areas in Singapore, collecting over 3.78 million readings. We present visualizations of mean signal coverage and RSCP CDFs for various areas of interest. The latter is a key output of Tattle, which helps operators to appraise coverage and solve the *CA* problem by relying on subscriber measurements, instead of expensive, laborious and limited-scale walk-/drive-tests.

***Keywords*— Cellular network management; Cellular coverage measurement; Participatory sensing;**

I. INTRODUCTION

The operating environment of cellular networks can be in a constant state of change. Due to evolution of the operating environment, operators may therefore have to regularly tune their networks so that cell service is not degraded. We interviewed a local operator in Singapore to better understand the challenges that they face in terms of network management. One of the key problems which they put to us is *coverage assertion* (*CA*): how can they efficiently verify that minimum coverage is met for an area of interest? Minimum coverage is defined by Singapore's regulatory authority to be a minimum threshold percentage of Received Signal Code Power (RSCP) samples (collected at a location of interest) which exceed -100 dBm. The RSCP is the received code power from the downlink Common Pilot Channel (CPICH), sent from base-stations [1].

The operator currently follows a manual approach. Areas with poor coverage are first identified through subscriber feedback. Coverage is then appraised by manual walk-tests, and if minimum coverage is not attained, parameters (such as pan, tilt and power) are iteratively tweaked. Such an approach is labor-intensive, expensive and limited in scale. The process has to be repeated whenever the operating environment evolves.

A. Paper contribution and overview

In this paper, we propose Tattle, a distributed, low-cost and comprehensive RSCP monitoring framework that addresses the *CA* problem in a scalable and real-time manner. Tattle has 3 key components, namely:

1. the local exchange of RSCP measurements between devices, and uploading of co-located readings to the network,
2. the pre-processing of co-located readings at the back-end to discard erroneously-localized measurements, and
3. the visualization of coverage based on collected RSCP measurements in specific regions-of-interest.

Tattle is designed to minimize operator expenses and labor, and monitor coverage in real-time on large geographical scales with good fidelity by removing erroneously-localized measurements. It enables operators to effectively appraise coverage without conducting expensive walk-/drive-tests. Operators can also proactively identify and mitigate spots with poor coverage in a timely manner, instead of reactively acting only upon subscriber complaints.

In Section II, we first describe the background of the *CA* problem, the approach which the operator currently takes, the difficulties they face, and why they desire a better solution. In Section III, we describe our proposed Tattle framework, and give details on the Tattle app and prototype. In Section IV, we discuss how readings can be pre-processed based on co-location to remove samples with location errors. In Section V, we describe our measurement collection procedures, and evaluate Tattle in terms of the localization fidelity of resulting measurements. We collected over 3.78 million RSCP measurements, and present real-world mean RSCP coverage maps and RSCP cumulative distribution functions (CDFs) of various areas in Singapore. Finally, conclusions and future work will be given in Section VI.

II. PROBLEM DESCRIPTION AND BACKGROUND REVIEW

Singapore's urban landscape is always rapidly evolving. The pace of urban development exceeds the operator's ability to keep up with network reconfiguration and infrastructure investment. The operator has to rely on subscriber complaints to discover areas that are poorly served. The regulatory authority in Singapore mandates that at least 85% and 99% of RSCP samples, collected within any indoor and outdoor area respectively, must exceed -100 dBm. If areas which fail these

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requirements are overlooked, the operator faces penalties by the regulator, and stands to lose subscribers to other competitors.

A. *Review of background literature*

The *CA* problem is loosely related to the problem of coverage estimation. The latter has a rich history of background work, yet because of the complexities of real-world deployments, existing proposed approaches find limited application. These approaches can be categorized into three groups, namely deterministic, stochastic and empirical. Deterministic models, such as ray-tracing [2], are used when the complete 3-D propagation environment is known. However, obtaining complete knowledge of the propagation environment is prohibitively expensive. Stochastic models are often used in coverage analysis [3]. While stochastic models are often analytically tractable, the assumed propagation models are often too generalized. Empirical estimation is based on empirical observations. We review this in detail as it is the approach currently undertaken by operators.

B. *Coverage assertion (CA): an empirical approach*

The operator typically finds out about areas with poor coverage through subscriber feedback. It may dispatch technicians to those specific localities to perform walk-/drive-tests with dedicated measurement and diagnostic equipment. The operator's main complaints about the current approach are that it is too labor-intensive, time-consuming, and expensive to conduct. Operating expense is high, yet a satisfactory survey of signal coverage is not guaranteed for two reasons:

1. it is prohibitively expensive to collect samples from all areas where there might be subscribers, and,
2. the readings collected by their measuring equipment may not directly reflect the coverage experienced by subscribers due to device heterogeneity.

Instead of a manual approach, the operator desires a system and framework in which quantitative measurements are collected, localized, and reported to the network by the UEs themselves, in real-time. In the literature, the following generic approach to coverage monitoring is commonly assumed. A typical operator may collect physical layer measurement reports from UEs [4], monitor cell-wide statistics [5] and alarms [6], perform periodic drive-tests to assert cell performance, as well as depend on subscriber feedback to determine if a cell is providing satisfactory coverage. However, our operator finds that directly relying on UEs' reported physical layer measurements has several drawbacks. We list them as follows.

1. The ability to gather measurement reports from UEs is tightly coupled with their abilities to obtain full cell service. For places which are very poorly-served, UEs often do not get a chance to send measurement reports.
2. Measurement reports are tagged with any location estimate that the UE may have. No additional effort will be imposed to refine location information [4][7]. Most reported measurements tend to have very coarse location information (e.g. somewhere within their cells) and are only useful for cell-wide analysis. GPS-based localization gives better location accuracy, but in our experiments, we observe some instances of egregious GPS errors, which affect the fidelity of RSCP measurements. We detail this in Section III.D.
3. Direct and frequent reporting of measurements can quickly consume UE power, as well as uplink capacity. We describe this in Section III.D.

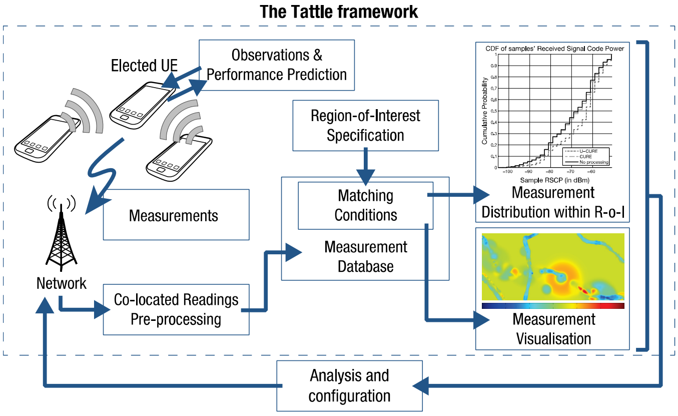


Figure 1: A diagrammatic description of Tattle, a distributed, low-cost and comprehensive cellular network measurement collection and processing framework. In this paper, we exemplify Tattle by leveraging on participating UEs to report on network coverage in real-time.

Due to these issues, the local operator which we interviewed does not depend on UE-reported measurements. Instead, they conduct manual tests where conditions (e.g. mobility, equipment used) are well-controlled, and measurements are tagged with precise locations. However, these results may not be representative of subscriber experience due to device heterogeneity. The geographic extent of their tests is also limited due to resource constraints.

RootMetrics [8] is a related commercial entity that aims to provide independent evaluations of networks through drive- and walk-tests conducted by a small number of hired 'scouts'. Our work differs critically from theirs in the following ways:

1. Instead of relying on a small number of hired personnel to collect measurements along pre-planned routes, Tattle devolves the responsibility of collection to subscribers whose true locations are mostly uncertain to the operator.
2. RootMetrics surveys a given area twice a year, while Tattle collects measurements in real-time, wherever there are participants.
3. The granularity of coverage maps produced by RootMetrics is in the order of hundreds of meters, while Tattle can produce coverage maps that are granularized to the order of meters, depending on the number of participants. This will be described in detail in Section V.

III. TATTLE – MONITORING THROUGH PARTICIPATION

We propose *Tattle*, a distributed monitoring framework that is scalable, minimizes manual labor and operator expense on drive-tests, monitors real-time coverage on a large geographical scale with good measurement location fidelity, and requires minimal involvement of subscribers (other than simply running a background app on their smart devices).

Figure 1 illustrates the overall system architecture of the Tattle framework. In the context of network coverage monitoring, there are 3 key components, namely:

1. the local exchange of RSCP measurements between devices, and uploading of co-located readings to the network,
2. the pre-processing of co-located readings to discard erroneously-localized measurements, and,
3. the visualization of coverage based on collected measurements in specific regions-of-interest.

A. *Benefits of low-power measurement exchange*

Subscribers are the best monitors of coverage wherever they are and wherever they require service. In our framework, the

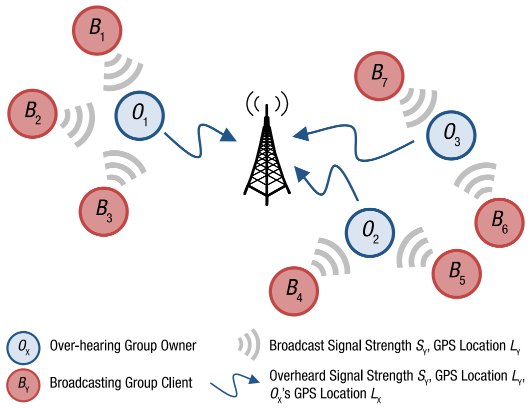


Figure 2: Participating users form local-area communication networks using interfaces such as WiFi Direct, to exchange signal strength readings. Elected Group Owners forward overheard readings to the network.

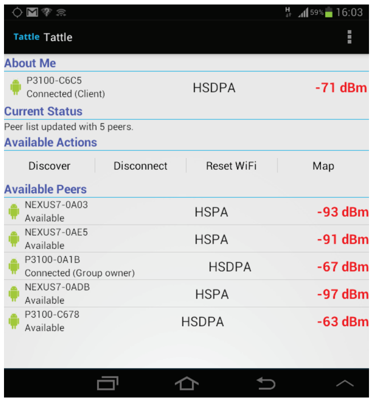


Figure 3: Screen capture of the Tattle app in operation. Nearby devices will be invited to join the network, and periodically exchange GPS location and signal readings.

UEs form distributed mobile sensor networks to monitor the RSCP experienced by each UE. Instead of purely relying on the cellular service to upload measurement reports, we advocate using low-power local communications (such as Bluetooth, or WiFi Direct) to exchange RSCP measurements between UEs. This preserves the co-locality of measurements and conserves UE power.

Conventionally, when a UE reports its measurement, together with its coarse location information, its measurement is taken in insolation. Two reports from separate UEs cannot be corroborated unless they have very reliable location fixes. However, if readings are exchanged through local communication, the principle of co-locality is preserved because a UE that overhears a report from another UE can be sure that the transmitter is within range (depending on the interface used). In our indoor range test experiment, we find that the devices used in our experiments (specifically the Asus Nexus 7's, and the Samsung Galaxy Tab 2 7.0's) can reliably receive each other's WiFi Direct broadcasts within 30 meters. In Section IV, we will use this communication range as an evaluation condition to determine whether an assessed reading should be admitted into the group of accepted readings, based on the knowledge that these readings were co-located. We can reject and discard a measurement if the reported GPS-location's distance to the admitted group is beyond local transmission range (in Section III.D, we report that GPS locations obtained by UEs in urban environments can often be significantly erroneous). *This is a key feature of Tattle*. Outdoor communication range may be higher, but we chose to use the observed indoor range of 30 meters as a conservative upper limit. This keeps the group of admitted measurements tightly clustered in space. We stress that the emphasis is on *keeping measurements that are likely to be well-localized, rather than admitting as many measurements as possible*. Figure 2 illustrates how the measurements can be communicated from UEs back to the network.

B. The Tattle app – Description and operation

The eponymously-named Tattle app is a simple prototype to demonstrate the efficacy of our proposed coverage monitoring framework. It exploits WiFi Direct™ [9] as a local communication interface for UEs to exchange RSCP measurements. Each device periodically broadcasts, per second, its GPS location, current network type (UMTS/HSPA/LTE), and the signal reading associated with its network type. In an active deployment, the sensing and broadcasting interval can be extended to automatically adapt to remaining battery power [10], current signal conditions, etc. A simple round-robin approach is used in our prototype to determine which UE in the network reports the next batch of overheard signal readings to the measurement database, but *our framework readily admits the use of other robust reporting schemes*. All uploads will be tagged with the timestamp of reception, and appended with the reporter's current GPS location.

We do not make use of Android's WiFi-assisted localization service as we found that it sometimes caused egregious errors in reported locations, especially in areas with WiFi routers configured as Extended Service Sets and sharing the same Service Set Identification (SSID). Since Google's Location Services ties a WiFi router's MAC address to a spatial location [11], we suspect that relocations of enterprise routers will result in some period of location confusion for UEs in those areas. Further investigation of this issue is beyond the scope of this paper.

Figure 3 demonstrates the Tattle app in action, with all 6 devices (as shown in the screenshot) connected to the same WiFi Direct network. In our experiments, all devices operate on one common provider's network. However, Tattle can be easily extended to work for devices served by different service providers, since local-area interfaces such as WiFi Direct are operator-agnostic.

C. Motivation for users

Oftentimes, when users experience poor or no signal coverage (as evinced by the display of 'signal bars' on most phones), they often ask: *is this phenomenon observed by others?* While knowing that others are experiencing similar coverage conditions does not necessarily help a user, it provides some level of comfort in knowing that the network, and not the user's equipment, is likely the source of the problem. On the other hand, if a user knows that most other subscribers are getting adequate signal coverage while his own signal readings are poor to non-existent, he can take some limited steps to alleviate the situation (e.g. restart his device, check his device settings, etc.).

To further incentivize subscribers to participate, recent studies have focused on monetary-based reward schemes that provide payouts to participants based on various criterions, such as their current locations [12], or their sensing contributions [13]. The operator can readily leverage on these mechanisms to instate a reward system by either providing subscription rebates, loyalty points, or handset discounts to incentivize participants.

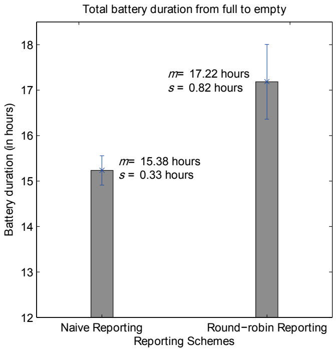


Figure 4: Battery drain test demonstrating the battery consumption of reporting methods.

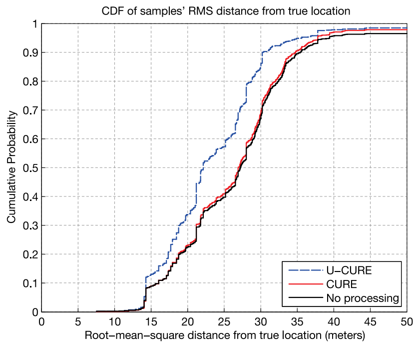


Figure 5: CDF plot of the root-mean-square distances of 18,191 static sample points from a known true location.

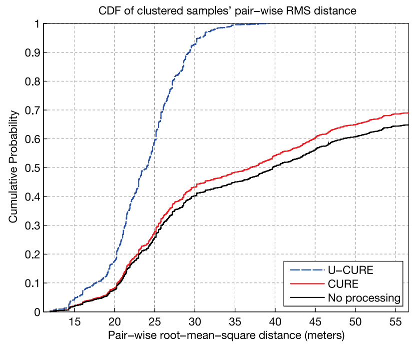


Figure 6: CDF plot of the pair-wise root-mean-square distance of sample locations known to be co-located from local-communication exchange.

D. *Tattle – power, and location uncertainty*

In Figure 4, we demonstrate results of battery drain tests conducted with 3 Samsung GT-P3100s. All 3 were first set to perform *naïve reporting*, where each device independently uploaded their RSCP readings and GPS locations every second to a remote server. The same experiment was repeated using Tattle's RSCP local exchange and round-robin network reporting approach. Each GT-P3100 broadcast its RSCP reading and GPS location every second. Using round-robin, each device reported all overheard measurements, including its own, for consecutively 20 seconds in every 60 second window. These two experiments were each repeated thrice. With naïve reporting, the devices lasted an average of 15.38 hours with a standard deviation of 0.33 hours. With Tattle, the devices drained completely after a mean of 17.22 hours with a standard deviation of 0.82 hours, lasting 12% longer on average. Further power savings are possible if more robust schemes other than round-robin are used, and the choice of the latter is simply for ease of prototyping.

We then conducted a ground-truth experiment at a known location to investigate the performance of GPS accuracy in an outdoor urban environment populated with low-lying buildings. We co-located 6 static devices, 3 of which are GT-P3100s and the other 3 are Asus Nexus 7s. The first several minutes of the experimental data were discarded in order to allow each device sufficient time to obtain a coherent GPS signal. In total, 18,191 samples were collected. 50% of these had mean locations more than 27.22 m off from the true location, while 2.79% had mean locations that were 2,877.69 m away from the known spot. The maximum observed discrepancy between a sample's mean location and the known spot was 2,996.07 m. Only 22.42% of measurements were less than 20 m distance from the true spot. Figure 5 shows the cumulative distribution function of the root-mean-square (rms) distances between the sample points and the known spot, before and after processing. In Section IV, we introduce the CURE algorithm, our extended U-CURE algorithm (which we used to pre-process the data in order to discard readings that are wrongly localized), as well as how rms distances are computed. After processing with U-CURE, the number of readings with rms location errors below 30 m saw a 17.85% improvement, compared to that of a naïve reporting approach, and a 16.19% improvement over CURE.

Figure 6 demonstrates the cumulative distribution of pair-wise rms distance between each sample-pair in each co-located batch of readings. Using the naïve reporting method, all context of co-location is lost. However, using U-CURE, we are able to exploit the knowledge of measurement co-location to discard samples that are likely to be erroneously-localized. All samples after U-CURE processing had less than 39.15 m rms pair-wise distances, while the naïve reporting method had pair-wise rms distances as high as 3,032.22 m, even though they were in reality physically juxtaposed.

E. *A note on security, privacy and trust*

In this paper, we focus on the systems aspect of our Tattle measurement collection and monitoring framework, and hence we omit, for brevity, comprehensive security, privacy and trust mechanisms in our Tattle prototype. However, we note the importance of having these mechanisms in an active, full-scale deployment, and briefly discuss some existing work in this area.

For Tattle, there are two primary concerns that we note:

1. Were the reported measurements actually observed by participating UEs, and not fabricated?
2. How can participating subscribers be assured of their anonymity and privacy?

With regards to the first concern, participants can lie about their measurement values, their purported locations, or both. For these cases, [14] suggests the possibility of using hardware-based solutions for trusted computing, such as Trusted Platform Modules (TPMs) [15]. As for the second concern, the authors in [16] propose a comprehensive reputation and trust framework to address the "trust without identity" problem. Tattle is flexible enough to incorporate these, as well as other ongoing security, privacy and trust research efforts.

IV. Hierarchical Clustering With Uncertainty

In a naïve reporting approach, the operator has to accept each report in good faith. However, the use of local measurement exchange guarantees that a mutually-overhearing device-pair is *surely at least within local communication range*. This context is important because it allows us to design techniques to discard patently incorrect reports that can otherwise affect the fidelity of the results. To this end, we propose U-CURE (*uncertain clustering using representative points*), an extension of the CURE clustering algorithm [17].

We chose to extend the original CURE algorithm because:

1. it is robust against outliers, and,
2. it identifies clusters that are non-spherical in shape.

The latter feature is especially desirable because the spatial distribution of participating devices does not conform to any particular shape. We stress that *our proposed framework readily admits other choices of pre-processing algorithms*, and the choice of U-CURE is intended to be instructive rather than exclusive. We make 2 important modifications to the CURE

Figure 7: The U-CURE algorithm.

```
function u_cure(S, k, max_dist)
% S is an input of N×3 matrix of N rows of [x,y,uncertainty] entries
% k is the desired number of clusters
% max_dist is the maximum expected distance allowed between clusters
1. Initialize C, a sorted array of clusters, each cluster has:
   a. list of points inside the cluster,
   b. a pointer to its nearest cluster,
   c. expected distance to nearest cluster,
   d. centroid in [x,y], simply the mean of all x's and all y's of points in C,
   e. a list of representative points for this cluster
2. Sort C according to ascending distances to nearest cluster
3. Initialize r, the number of representative points that represents each cluster
4. While length(C) > k,
     if distance of cluster C{1} to the next nearest cluster is > max_dist,
       break;
     else
       merge top two clusters of C;
   endwhile

function merge_clusters(C, r)
1. Sort C according to ascending distances to nearest cluster
2. merge the first two clusters of C,
3. evaluate centroid of the newly merged cluster,
4. find the representative points of the newly merged cluster,
5. re-compute expected distance between every cluster-pair and re-sort C

function find_rep_points(p, centroid, r)
  % p is the complete set of points in the cluster that we want representative points for
1. if length(p) ≤ r
     return p,
   else
     set the first representative point as the point furthest from centroid
2. while length(rep_points) < r,
     find the point from p whose min. distance to other rep_points is max
     add that point to rep_points and clear it from p
return rep_points
```

algorithm to handle the reported uncertainty in a measurement's location, as well as to discard samples with likely incorrect locations. We refer to the modified algorithm as U-CURE, and a sketch of the U-CURE algorithm is given in Figure 7.

A. U-CURE: Extending the original CURE algorithm

We first briefly describe the CURE algorithm [17]. CURE considers each data point as a point source in Cartesian space. The distance between two clusters A and B is the minimum distance between all the possible representative point-pairs. It works as follows:

1. Start by considering every point as a separate cluster.
2. Merge the two clusters that are closest in distance.
3. Find n representative points of the newly merged cluster, where the first point chosen is furthest from the centroid, and each subsequent point is chosen sequentially such that its minimum distances to all previous representative points is maximum.
4. Repeat Step 2 and Step 3 until the desired number of clusters remain.

At the conclusion of CURE, we pick the largest cluster as the set of admitted points, and discard the rest. We extend CURE in 2 important ways to further improve clustering accuracy. First, we implement a stopping condition: when the closest two clusters have an rms distance larger than the maximum range of the local communications interface, they should not be merged and the algorithm should stop. This corresponds to the *max_dist* condition in the algorithm. Since we are interested in the cluster with the largest number of sample points most closely located together, we set the desired cluster parameter k as 2, where we keep the primary cluster and discard the secondary, out-lying cluster. The *max_dist* condition then terminates U-CURE clustering early if clusters are too far apart to be co-located. In doing this, *we exploit the knowledge of co-location garnered through local measurement exchange*.

Next, unlike the assumption of location *certainty* in CURE, GPS locations in Android are given as a 3-tuple of latitude, longitude, and uncertainty. This uncertainty is expressed as a σ value in meters, and modeled as a 2D normal distribution with the mean location given by the latitude and longitude. In order to extend CURE to take into account the uncertainty of sample locations, we consider the *expected square-distance* between uncertain location points, instead of just the distance between their means. We formalize the evaluation of the expected square-distance between two uncertain location points as follows.

Lemma: The expected square-distance between two samples $U = (X_U, Y_U)$ and $V = (X_V, Y_V)$, centered in Cartesian space (X_U, Y_U) and (X_V, Y_V) respectively, where $X_U \sim \mathcal{N}(x_U, \sigma_U^2)$, $Y_U \sim \mathcal{N}(y_U, \sigma_U^2)$, $X_V \sim \mathcal{N}(x_V, \sigma_V^2)$ as well as $Y_V \sim \mathcal{N}(y_V, \sigma_V^2)$, is equal to $2(\sigma_U^2 + \sigma_V^2) + (x_U - x_V)^2 + (y_U - y_V)^2$.

Proof: Let $X = X_U - X_V$ and $Y = Y_U - Y_V$. Since the difference of Gaussian R.V.s is also normally distributed, we know that $X \sim \mathcal{N}(x_U - x_V, \sigma_U^2 + \sigma_V^2)$, $Y \sim \mathcal{N}(y_U - y_V, \sigma_U^2 + \sigma_V^2)$. Let $D = X^2 + Y^2$, and $D' = (X/\sigma_X)^2 + (Y/\sigma_Y)^2$. Since X and Y are normally-distributed and independent, the sum of their squares normalized by their variances is represented by the non-central χ^2 distribution, where $D' \sim \chi^2[k = 2, \lambda = (\mu_X/\sigma_X)^2 + (\mu_Y/\sigma_Y)^2]$. Using the known result $\mathbf{E}(D') = k + \lambda$, and after some after some rearrangement, we obtain $\mathbf{E}(D) = 2(\sigma_U^2 + \sigma_V^2) + (x_U - x_V)^2 + (y_U - y_V)^2$. ■

This lemma is an important one because it allows us to easily evaluate the numerical result of the expected square-distance between any two samples without having to evaluate any computationally-expensive integrals. This makes U-CURE more efficient in terms of computation. By taking into consideration location uncertainty and measurement co-location, U-CURE enables the pre-processing of co-located readings to discard samples that likely to be mis-localized.

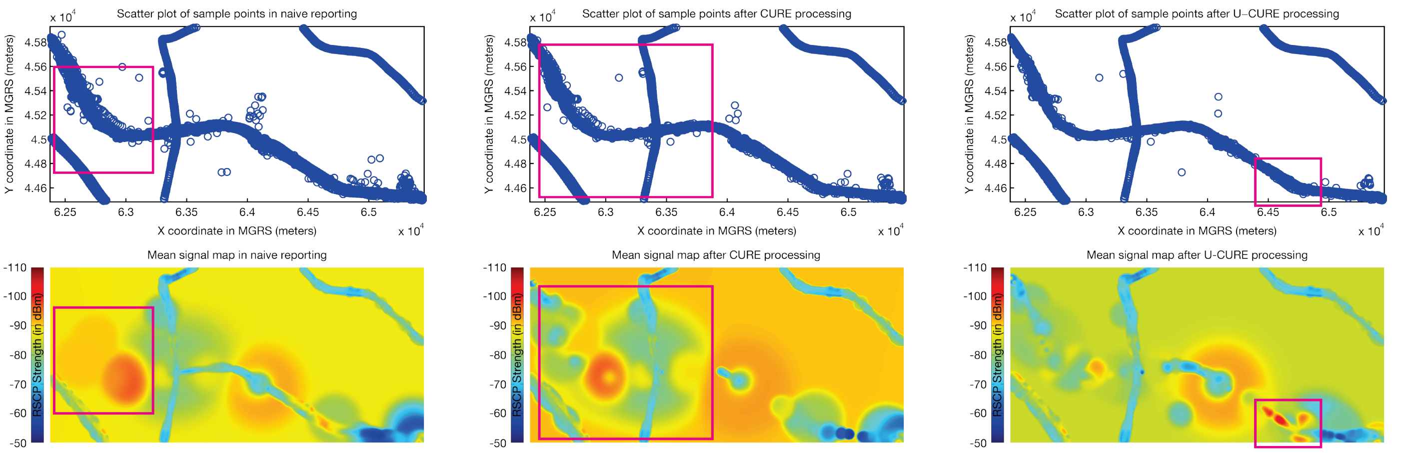
V. Measurement Collection, Processing, And Signal Coverage Representation With U-CURE

In this section, we describe the third key component of Tattle: the visualization of coverage based on collected RSCP measurements in specific regions-of-interest. We conducted extensive RSCP measurement collection over the course of more than 4 weeks, gathering over 3.78 million samples. 6 tablets were used in our experiments, namely 3 GT-P3100s, and 3 Asus Nexus 7s. All 6 tablets were always co-located and maintained WiFi Direct connections to one another. Collection of data points was done throughout the day, in all kinds of environments.

A. Mean coverage visualization

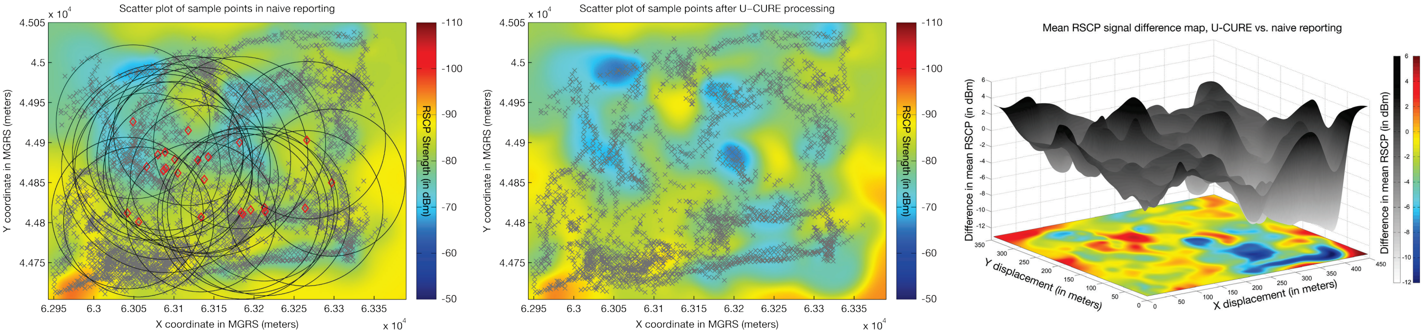
In Figure 8, we first illustrate the efficacy of Tattle in the mass-collection of data points, particularly on Singapore's rail system and roads. The plots of mean RSCP maps should be of particular interest to cellular operators, who will find difficulty in achieving this scale of sampling by performing walk-/drive-tests. Our framework enables this by allowing participating UEs to undertake the task of coverage monitoring. These maps are obtained as follows:

1. taking every sample point and weighing its RSCP value with a 2D Gaussian filter, centered at the sample's reported mean, with sigma value equal to the sample's σ uncertainty,
2. summing up the resulting 2D matrix generated for each measurement, and,
3. compute the weighted average for every 1 m by 1 m bin.



(*a*) (*b*) (*c*)

Figure 8: The figures above represent the individual cases of (a) naïve reporting, (b) standard CURE and (c) U-CURE respectively applied to 39,947 sample points in the region (1.307, 103.763) to (1.320, 103.791). Top row of figures represent the scatter plot of sample points' mean position in each individual case. Bottom row of figures represent the mean signal map (where orange to red regions represent areas of barely- to unacceptable coverage, i.e. -90 dBm to -110 dBm, and blue to yellow regions represent regions of excellent- to barely acceptable coverage -50 dBm to -90 dBm). Areas of interest are marked out with rectangles.



(*a*) (*b*) (*c*)

Figure 9: The figures above represent the individual cases of (a) naïve reporting and (b) U-CURE, respectively applied to 30,352 samples in the region (1.309, 103.768) to (1.312,103.772). This sub-region was chosen from the above region to highlight the importance of removing wrongly-localized sample points. The 1-σ uncertainty radii were plotted for points with location uncertainty exceeding 90 m. Figure (c) represents the spatial plot of differences in the mean RSCP maps observed in (a) and (b).

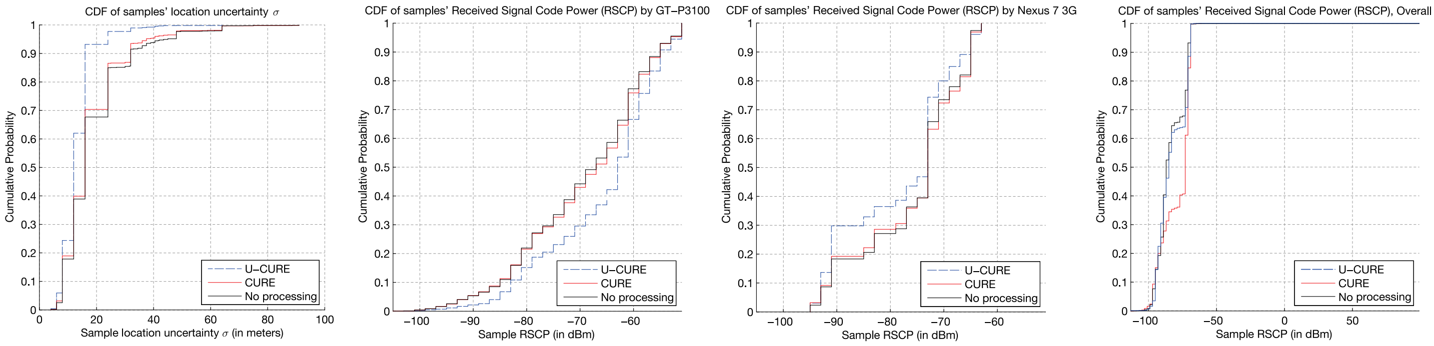
The corresponding scatter plots of measurements for naïve reporting, CURE and U-CURE are juxtaposed. In reality, all of the sample points should lie on the main veins, which correspond to high-speed rail tracks and roads. In both the naïve reporting and CURE approaches, we see the debilitating effects of stray signal points with especially large uncertainties in the highlighted areas. They pollute the overall signal map with large blobs of measurements (due to their large values) that extend way beyond the main veins, and causes measurements with high location accuracies (and correspondingly low values) to be averaged out. We term this as the 'smirching' effect. Interesting features, which are specific areas with either excellent or unacceptable coverage are difficult to spot.

This poses a problem for operators as they require a high degree of fidelity to identify specific problem areas. In contrast, U-CURE processing removed most of the mis-localized points and reveals a significant coverage hole demarcated at the bottom right. Localized features are more accentuated with much less 'smirching' blobs.

In Figure 9, we present mean RSCP signal maps, overlaid with scatter plots for a newly-developed area which is known to have poor signal coverage. The 1-σ uncertainty radius for measurements with exceeding 90 m were also plotted for illustration purposes. Without processing, the signal map has indistinct features that appear 'smirched' and averaged out. This is evident by the existence of large numbers of points with high location uncertainty. However, after applying U-CURE to discard polluting points with large location uncertainties, the areas that had either excellent coverage or poor coverage are now clearly demarcated. No remaining measurements had σ exceeding 90 m. Figure 9(c) shows the differences in the mean signal map between U-CURE and naïve reporting. U-CURE reveals that some areas had worse RSCP reception by up to 5.23 dBm compared to naïve reporting, and better reception in others by up to 10.06 dBm. These differences will otherwise be 'smirched' out by large uncertainties in naïve reporting. We remark that these are mean spatial RSCP maps, and hence areas with only barely-acceptable mean coverage will most likely fail the minimum coverage requirement described in Section II.

B. Region-of-Interest based CDF derivation

In Figure 10(a)-(c), we present another representation of signal coverage that allows cellular operators to directly solve the *CA* problem. In this figure, the cumulative distribution of RSCP readings, rather than just the mean, is illustrated for an urban outdoor area. Figure 10(a) represents the distribution of 34,837 RSCP measurements' location uncertainty collected over the 187 m x 374 m area. U-CURE processing results in a 25% increase of points with under 20 m uncertainty. We see another dimension of analysis when we separate the data by the type of reporting device. In all of our experiments, we observed that the GT-P3100 reports RSCP measurements very responsively, and the delta of consecutive RSCP measurements is often as small as ±1 dBm within a space of 1 second.



(*a*) (*b*) (*c*) (*d*)

Figure 10(a)-(c): The figures above represent the cumulative probability distribution of (a) the 1- σ location uncertainty of sample points before and after processing, (b) RSCP for GT-P3100s in the same area, and (c) RSCP for Asus Nexus 7s in the area, constructed from 34,837 sample points in the region-of-interest from (1.332, 103.741) to (1.335, 103.743). (d) Indoor residential area, where Tattle's effectiveness is tapered.

However, the Nexus 7s tend to be comparatively sluggish and often go tens of seconds or more without reporting any change in RSCP, even when mobile. This can either be due to a driver implementation issue (e.g. a large smoothing window) or hardware differences (in terms of antenna size, build and quality). The ability for Tattle to be extended to include device make and model in RSCP reporting is especially useful for operators, which have to support a plethora of mobile devices on their networks. Knowing that a model of UE is particularly problematic helps the operator in making either network (e.g. increase cell tower antenna coverage at places with higher number of these devices) or business (e.g. present explicit caveats to consumers buying problematic devices) decisions.

C. Current limitations of our prototype

Figure 10(d) illustrates the RSCP distribution of measurements collected in an indoor environment. In these cases, GPS localization works poorly. There is no basis to keep or discard any particular data point, as their uncertainties, and hence their rms distance between one another, even when co-located, is often very large. Hence, there is little difference between the results of naïve reporting and U-CURE. However, we remark that in terms of measurement location fidelity, naïve reporting forms the lower bound of performance, and Tattle will not perform worse. To address this limitation, we intend to extend Tattle to include other dimensions of location information to address the limitation observed indoors, e.g. by allowing volunteer input, suggesting possible lists of locations to select from using historical likelihood, and so on.

VI. Conclusions And Future Work

In this paper, we describe *Tattle*, a comprehensive, large-scale cellular network monitoring framework, which we exemplify by leveraging on participating UEs to address the *CA* problem. The Tattle framework relies predominantly on opportunistic inter-UE measurement exchange to preserve the co-location of measurements and conserve UE power.

We show through experiments that in urban built-up areas, GPS locations reported by UEs may have significant uncertainties and can sometimes be several kilometers away from their true locations. We describe how U-CURE can take into account reported location uncertainty and the knowledge of measurement co-location to remove erroneously-localized readings.

We then illustrate several real-world representations of signal distributions that are of interest to cellular operators. These are made possible through the Tattle monitoring framework. When deployed on a large-scale with sufficient participants, operators can minimize their operational costs of conducting manual walk-/drive-tests. They can also proactively mitigate poor coverage conditions in a timely manner, instead of depending on subscriber complaints after the fact, which can often be vague and subjective.

For future work, we expect to extend Tattle to monitor cellular service quality, in addition to just downlink signal reception. We will also focus on ways to enhance performance in fully-indoor environments.

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