Impact of Device Diversity on Crowdsourced Mobile Coverage Maps

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***Abstract*—Mobile coverage maps increasingly rely on user-side measurements such as those collected from crowdsourced mobile apps. These measurements inherently span a multitude of devices, differing in models and vendors, with different radio signal reception characteristics. We show measurement based evidence on the significant deviations in received signal strength distribution seen by different devices, all other factors being equal. More crucially, we examine the accuracy of coarse-grained/fine-grained measurement based mobile coverage maps as seen from a device's perspective. Our key finding is that mobile coverage maps based on measurements from a diversity of devices are still fairly reliable from a device's perspective so long as it is among the set of devices used to collect measurements. Our study also offers guidelines on ways towards reliable measurement based mobile coverage maps in presence of device diversity.**

***Index Terms*—Device diversity, mobile coverage maps, RSSI measurements.**

I. Introduction

Knowledge of mobile network coverage is beneficial both to operators and users. It guides operators on areas where either deployment of additional infrastructure or configuration changes (e.g., height, tilt and power) of deployed base stations are needed to fill coverage holes. Users can make a better selection of operator based on coverage in their area of interest.

A common practice for operators is to use their infrastructure information and measurement based models to provide coverage maps of their networks on their respective official websites such as in [1] and [2]. Measurements to aid in this process are collected either with drive testing or increasingly via low cost user-side approaches like crowdsourcing [3]. The reported maps on such sites typically only display maps per radio-mode (2G/3G/4G) and are coarse grained in which they showcase either a boolean representation of signal quality namely 'weak' and 'strong' signal or on an unknown scale of 'low' to 'high' value at per postcode level such as in [1]. Same can be said about the granularity of information provided by third party mobile coverage mapping sites such as OpenSignal [4]. Alternatively, the signal quality over space can be mapped in a fine-grained manner. A state of the art method for such mobile coverage map generation is to collect RSS measurement samples at some parts of the region of interest and interpolate signal quality at the unobserved parts.

With the proliferation of different smartphone models from different manufacturers in the market [5, 6], the question is how well the above outlined types of coverage maps represent the mobile coverage perceived by different devices when all other factors remain the same (operator, cell, location, etc.). In other words, how accurate is the coverage map from any given device's perspective? This is a significant issue given the multitude of device types users carry and being used for collecting signal strength measurements, especially for crowdsourced coverage maps. While the issue of device diversity impact and mitigation has been previously studied in the context of indoor localization based on Wi-Fi fingerprinting, the setting of mobile cellular networks and coverage mapping has its own peculiarities, as discussed in the next section.

In view of the above, this paper studies the impact of device diversity on measurement based mobile coverage maps, especially those relying on crowdsourced measurements. It also examines the reliability of a coverage map generated using measurements collected from a large pool of diverse smartphone devices, locations and times from the perspective of a given device, which may or may not be represented in the set of measurement devices. In particular, using a large real-world crowdsourced mobile signal measurement dataset with over million measurements spanning an year from 80 different devices, we study:

- how well the coarse grained mobile coverage maps available from official websites of operators and crowdsourced coverage mapping sites correlate with coverage experienced for a given device type?
- how well measurements from different device models from the same vendor reflect the fine grained coverage status seen by any of those devices?
- the impact on coverage map accuracy when measurements come from devices across multiple vendors.
- how useful measurements from an earlier time span are to assess coverage map accuracy for a device at a future time?

Our key finding is that so long as a given device is among the set of devices contributing measurements underlying a coverage map, even if the measurements are from a previous time span, the map is reliable from the device's perspective. Our study also reveals guidelines for producing reliable mobile coverage maps in presence of device diversity. To start with, we also provide measurement based evidence to demonstrate the impact of device diversity on received signal strength distribution in both controlled and crowdsourced settings.

II. Background and Related Work

A. Factors Impacting Device Signal Quality

The large variation in devices and their characteristics result in varying degree of signal qualities at a given location even

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if served by the same cell of the same mobile network operator. For example, a study commissioned by the UK regulator Ofcom tested sensitivity level of ten different devices under different radios and frequency bands in free space and observed variations in their received signal strength (RSS) values [7]. There are in fact a number of reasons [7, 8] for this variation including but not limited to: (a) **antenna design**: whether an internal or external antenna is used and its size can affect the gain of the device antenna; (b) **device design**: materials of different devices can have different absorption effects on radio signals; (c) **RF receiver design**: noise and nonlinearity at receiver circuitry of the device can affect the performance; and (d) **number of frequency bands supported**: as more frequency bands are added to the device antenna the receiver design becomes more complex, which can make it more difficult to achieve good signal quality. There are some other impacting factors for signal variation such as user's mobility, orientation of device, humidity and temperature but these can affect all types of devices.

B. Related Work

Impact of device diversity has previously received attention from the research community but in the context of Wi-Fi fingerprinting based indoor device localization [9–15]. Broadly speaking, these studies [10, 13, 14] resolve the effect of signal strength variation across diverse devices via either calibration based or calibration-free methods.

In calibration based methods [10, 12], before locating an end-user, the RSSs from the surrounding APs are calibrated into readings similar to the device with which fingerprint database is generated, using a technique like pair-wise linear transformation. These methods however assume that sufficient measurements for a set of locations per device-type are collected a priori so as to derive an accurate mapping function; as such they may fail when a new previously unseen device emerges.

On the other hand, in calibration-free methods either relative RSS values of the sensed APs are used as in [11, 14] or APs are ranked according to their RSS values [15]. The relative relation or ranking is then used to locate end-user accurately avoiding the bias introduced by differences in the devices' RSS readings.

From the perspective of crowdsourced cellular signal strength measurements, neither calibration-based methods nor calibration-free methods are applicable. As cellular networks span over large geographical areas with variety of terrain properties, there is a small probability to have multiple measurements from all foreseeable devices for the same set of locations under similar environmental conditions, thus making it difficult to apply calibration based methods. Additionally mobile applications used for obtaining crowdsourced measurements in practice have only access to RSS readings from only the serving cell tower, thereby making it impossible to use calibration-free methods.

Towards reliable outdoor WLAN radio map construction with diverse devices/measurements, noise cancellation approaches have been studied [16, 17]. X. Fan et al. [16] propose a model-driven approach for taming heterogeneous noise generated by devices to produce a reliable radio map. Similarly, C. Xiang et al. [17] proposed CARM, a method to mitigate the effect of error-prone and inaccurate crowd-sensed readings from crowd devices, to build better outdoor WLAN RSS maps. While the works of [16, 17] propose building of a single noise-free coverage map by dealing with noise or RSS variation that come with diverse devices, they do not examine the accuracy of the coverage map from the perspective of a device.

Towards reliable measurement based mobile coverage map generation, there exist several studies that address issues like:

- Filtering out samples with wrong GPS locations [18] or minimizing negative impact of unfavorable characteristics including location inaccuracy, non-uniform measurement distribution and sparse samples by proposing use of a robust interpolation process [19],
- Devising RSS estimation schemes that end up in reliable coverage map at unobserved locations [20, 21],
- Using a sampling strategy so that reliable mobile coverage maps can be generated with minimal measurement overhead [22, 23].

C. Datasets

For our study, we use a large crowdsourced measurement dataset for London from OpenSignal [4] spanning an year between 2012 and 2013. This dataset consists of measurements for two major UK mobile network operators, henceforth referred to as `Operator1` and `Operator2`. It consists of over 1.129 million samples from 80 different device-types, largely from two vendors (Samsung and HTC). In terms of the radio mode, we focus on samples for 3G/HSDPA mode. RSSI values in the dataset are represented in arbitrary signal unit (ASU), which is an integer value proportional to the received signal strength measured by the mobile phone [24]. For evaluating different scenarios, we used samples belonging to different models from Samsung and HTC vendors unless stated otherwise. In each scenario, we have tested combinations of devices from these two vendors including GT-i9100, GT-i9300, GT-i9300P, GT-N7100, GT-N7105, HTC Desire, HTC ONE S, HTC ONE X, HTC EVO 3DX 515m, HTC Sensation 2710e, and Galaxy Nexus. The paper however presents results corresponding to one such combination of these devices in each test case.

D. Methodology and Performance Metrics

To assess the accuracy of coarse-grained coverage maps (with few discrete levels of signal quality like weak and strong) from a device's perspective, we use *Overlap Coefficient*, a similarity metric that measures the overlap between two sets.

For fine-grained measurement based coverage map generation, we rely on Ordinary Kriging (OK) which has been shown to be a robust spatial interpolation scheme [19, 25] for crowdsourced measurements. And to assess the accuracy of such fine-grained maps we use *mean absolute prediction error (MAPE)* as the performance metric.

III. Device-centric Assessment of Coverage Map Accuracy

To understand the impact of device diversity on cellular RSS distribution, we take two case studies with measurements collected at same location by two different device models connected to same network and cell sector. In the first case, we collected samples by holding the two devices side-by-side whereas in the second scenario, samples are from OpenSignal dataset collected at Edinburgh, UK. Fig. 1 demonstrate that in both these controlled and crowdsourced measurement scenarios, different devices vary in their RSS distributions, all other factors remaining similar.

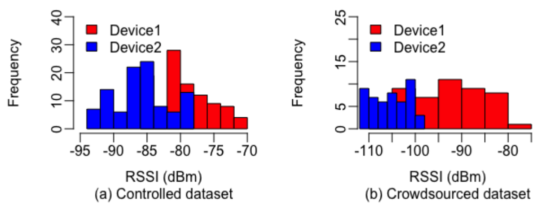

Fig. 1. Variation in RSSI distribution due to device diversity.

RSS variation from diverse devices impacts accuracy of resulting radio coverage map of a network. From a device's perspective its experience with a network has low similarity with the combined coverage map if the latter is generated ignoring samples from that device model. We demonstrate this by interpolating a combined coverage map, applying OK, both on measurement sets including and excluding samples from the test device. Table I shows that ASU MAPE at test locations from that of a test device is higher when the generated combined radio map does not consider samples from the device model in question. We see substantial drop in error for different test devices when the samples from test device are included while generating a combined coverage map.

TABLE I
Similarity with Combined Mobile Coverage Map

Method used	**Operator1**		**Operator2**	
	Device 1	***Device 2***	***Device 1***	***Device 2***
Mean absolute prediction error with fine-grained coverage map				
Not Included	4.49	7.28	4.92	5.69
Included	2.94	4.64	2.96	3.72
% Drop	34.5%	36%	39.8%	34.6%
Overlap coefficient with coarse-grained coverage map				
median RSS	81%	40%	70%	65%
max. RSS	95%	60%	77%	74%

A. Correlation with Coarse Grained Coverage Map

High ASU MAPE difference with the two variants of fine-grained coverage maps suggest assessment of coarse-grained coverage map that is generally displayed by operators and crowdsourced databases as a guide for customers. These maps present coverage quality in either a coarse boolean scale of weak-strong or 5-scale metric of low-to-high. Some other methods include a general description of what MBB services are available or if coverage is available indoors and outdoors. The geographic granularity of the displayed coverage information is also at coarse level of postcode. We are interested in seeing how well correlated such a map can be when samples from device-type in question are not used in deriving the map.

We take a rectangular area of central London and divide it into grids of 50 sq. meter. We then specify if a grid has 'weak' or 'strong' signal on the bases of median/maximum RSSI of its enclosed samples. For 3G, OpenSingal considers a signal as weak if below -99 dBm and strong if above -85 dBm within a range of -51 to -113 dBm. Since in our dataset signal strength values are in ASU with range 1 to 20, we tag signals below 9 ASU as 'weak' and those above as 'strong'. For evaluation we take test devices from two different vendors from each of the operators i.e. `Operator1` and `Operator2`.

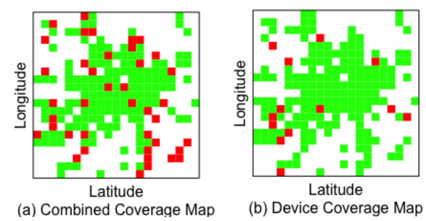

Fig. 2. Part of a coarse radio map with weak (red) and strong (green) RSS samples generated with (a) measurements from devices (other than test device) and (b) samples from the test device.

Fig. 2 displays a combined coarse map (ignoring samples from test device) and a device specific coarse-grained map with tagging done on median RSS per grid. Complete similarity results from this method are presented in Table I, here we observe overlap coefficient is relatively higher for Device1. This may be because most samples in dataset are from the vendor of Device 1 with 47% & 56% share in datasets from `Operator1` and `2` respectively, where for the vendor of Device 2 this share is 9% and 14%. Secondly correlation improves substantially when instead of median, tagging uses maximum RSS per grid which however biases radio map towards good network availability. The similarity drop from Device 1 to Device 2 verifies that a single combined coverage map cannot well represent coverage status observed at a test device when it lacks measurement samples from the device.

B. Impact of Different Measurement Sources on Fine Grained Device-Centric Coverage Map

A fine grained coverage map is desirable for correct decision making e.g. it spots out exact places where network faces connectivity loss helping operator to know the cause (e.g. a new building) and to act promptly for remedy. It assists users in finding places in residential and work area where network connectivity is seamless. A fine grained map gives out signal strength in true units at the granularity of longitude and latitude. With the goal to maximize accuracy of such a map, from the perspective of a device-type, in following subsections we assess and identify the order of preference in which samples from different crowdsourced sources can be used.

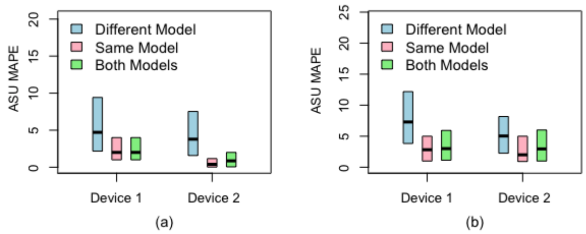

Fig. 3. ASU MAPE with measurements from different, same and both device models using (a) `Operator1` and (b) `Operator2` datasets.

Samples from different device-model Taking different case-studies we find that using measurements from a different device-model always produce a higher prediction error compared to when using measurement samples from same device-model. Fig. 3 illustrates results from two such devices. In each of the three cases, per test device, the calibration set size is constant with samples from cells where test device samples are available. A key observation here is that using different device-model's measurements in conjunction with samples from same device-model does not degrade accuracy considerably.

Samples from different device-vendor The accuracy worsens as samples from different device vendors are used to predict radio coverage status at a test device. Fig. 4 demonstrates it with results from devices belonging to two different vendors. We see that use of different vendor generally raises prediction error by a higher percentage indicating to avoid using samples from different vendors when generating coverage map for a device, lacking samples.

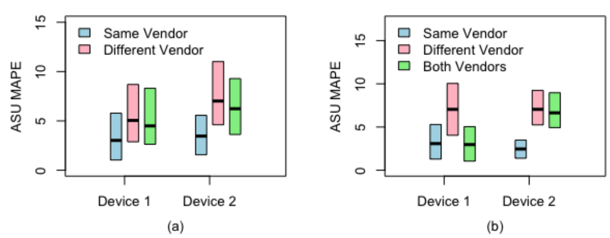

Fig. 4. ASU MAPE with samples of devices from same and different vendors using (a) `Operator1` & (b) `Operator2` datasets.

Samples from past time-span To see value in samples collected in past time-span we use it in conjunction with measurements from 'target' time-span, a period for which coverage map of a device is desired. For the purpose of illustration, here we have split datasets from both the operators in half on the basis of measurement reporting time.

Just like impact of using measurements from different device-model, here too we find that measurements from past does not add to the accuracy of a coverage map, but when used separately produces higher error. Fig. 5 show results from two device models from each operator's dataset. Use of measurements from previous time span raises error above 50% with slight raise when measurements from both same and previous time span are used, recommending to use recent samples where possible.

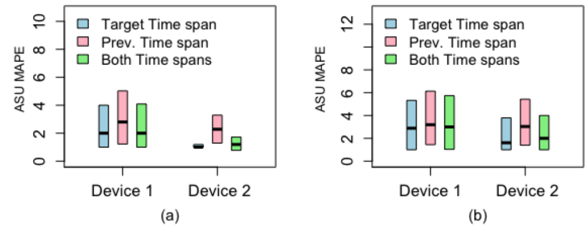

Fig. 5. ASU MAPE with samples from target, previous and both the time spans for two device-types using (i) `Operator1` & (ii) `Operator2` datasets.

Previous coverage information vs different device-models If generating a device-centric coverage map two sets of samples are available i.e. samples from previous time-span with same device model and from same time-span but different device model, the results in Fig. 6 show that the good choice is to use previous information from same device-model.

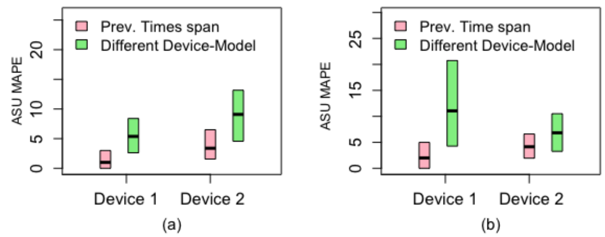

Fig. 6. ASU MAPE with samples from previous time-span but same device-model and with different device-model but for same target time-span using (i) `Operator1` & (ii) `Operator2` datasets.

IV. Conclusion

Impact of device diversity has been studied widely in the context of Wi-Fi fingerprinting based indoor device localization; here pre-processing on RSS readings from different devices is performed to locate a user accurately. No such preprocessing is, however, applied when generating a mobile coverage map with crowdsourced measurement samples, partly because it is infeasible to do so in the wide-area cellular network setting with measurement samples coming from not only a large pool of diverse devices but also from diverse locations and at different timings. Our measurement based analysis study has focused on the coverage map accuracy from the perspective of a device-type when the map is generated using measurements from diverse sources. We find that the percentage raise or drop in performance is highly variable across different scenarios; however the general trend is that measurements from same device-model and same time-span always results in better coverage accuracy, followed by samples collected with same model but at different time-span e.g. previous year. For different models, we observed that if they are from the same vendor the error is lower than when samples are from different device vendors. Furthermore our results show that if samples form different device-models and time-spans are used in conjunction with test device-model's samples, the drop in accuracy is marginal. We have also studied the correlation between coarse grained coverage map based on measurements from different devices with that of the map corresponding to a particular device.

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