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Mapping WiFi measurements on OpenStreetMap data for Wireless Street Coverage Analysis

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ABSTRACT:

The growing interest on smart cities and the deployment of an ever increasing number of smart objects in public locations, such as dumpsters, traffic lights, and manholes, requires ubiquitous connectivity for these devices to communicate data and to receive configurations. Opportunistic WiFi connectivity is a valid alternative both to ad hoc solutions, like LoRa, which require costly deployments, and to communicating through the mobile network, which is both pricey and battery power hungry. In this paper we present a tool to analyze the WiFi coverage of home Access Points (AP) on the city streets. It can be of interest to ISP or other providers which want to offer connectivity to Internet of Things smart objects deployed around the city. We describe a method for gathering WiFi measures around the city (by leveraging crowdsourcing) and an open source visualization and analysis web application to explore the accumulated data. More importantly, this framework can leverage the semantic information contained in OpenStreetMap data to extract further knowledge about the AP deployment in the city, for example we investigate the relationship between the AP density per square kilometer within the city and the WiFi street coverage ratio.

1 Introduction

WiFi access points (APs) are ubiquitous in urban areas. WiFi enabled areas can be found in every part of modern cities: university campuses, shops, hotels, stations, airports, workplaces, and private households. In these environments the WiFi network provides Internet connectivity to a wide range of apparatuses ranging from personal devices (e.g, tablets, smartphones, and laptops) to generic networked appliances within homes and businesses premises. However the APs coverage cannot be confined within the site walls and it often covers also the surroundings, thus other (outdoor) devices in the street can sense and make use of the WiFi signal.

In most of the cases these APs are private and indoor, thus not open for association to whoever happens to come along. However in some cases, if their owners are members of a "Community Network" (CN), these APs may share their Internet access with other members of the same community using a common open-system authentication framework. This concept of sharing residential DSL access was originally proposed by FON (FON) and now it is adopted also by other companies such as WiFiTastic in San Jose (WiFiTastic), Orange in France (OrangeHotspots), Vodafone in Europe (VodafoneWiFiCommunity), etc. Because users willing to access the CN service while away from home are required to also share their own Internet access with other subscribers, there is no additional charge for the service. Other business models may however allow access to users outside the community for a fee, for example, Skype WiFi (SkypeWifi) users may pay to access FON and some other ISP APs around the world.

Going beyond the common scenario of providing Internet access to mobile devices and travelling users, the extension of APs coverage outside their owner's premises to the surrounding public spaces may be exploited also by a wide range of other devices. Along with the recent developments of WiFi technology towards low power and long range (WiFiHaLow), Wi-Fi has the potential to become a ubiquitous standard also for the Internet of Things (IoT). In fact, a multitude of potentially WiFi capable devices spread around the cities in the public spaces (e.g., traffic lights, dumpsters, pollution monitoring equipment, etc.) are already under the coverage of some residential AP that can give them Internet access at low or no cost. For example, residential

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DSL modems equipped with a WiFi router may enable ISP to provide connectivity not only within the house walls, but also to the network enabled intelligent "things" that are outside.

However, in order to assess the coverage of public areas by residential APs, we need to know the WiFi signal strength in each possible location within a city. Since this information is useful also for other services such as device localization and cellular network data offloading, several studies have investigated the problem and open databases came up allowing access to the dataset of the collected measures. OpenBMap (OpenBMap), WiGLE (WiGLe), OpenWLANMap (OpenWlanMap), and OpenSignal (OpenSignal) gather data from tools, i.e., war-driving applications, distributed to users for different platforms (e.g., smartphones), that are used to perform passive WiFi APs discovery while walking, riding or driving.

In this paper we present a novel use of such information to characterize the amount of WiFi APs coverage in the streets of a city by combining croudsourced measurements with OpenStreetMap (OpenStreetMap) information on the streets topology. Since APs are deployed indoors and in an unplanned manner, we investigate if their coverage is sufficiently dense, if such an architecture is feasible, on what conditions depend its performance, and what type of applications may benefit from its services.

We also show the results for the city of Turin, Italy, and highlight the impact of the dissemination of WiFi APs on an IoT scenario. This is a more precise technique to estimate the coverage of CNs with respect to the raw number of deployed APs per square kilometer.

The software for wireless street coverage analysis that can map WiFi measurements on OpenStreetMap data to visualize and estimate the wireless connectivity on the streets is available, as open source software, on the GitHub platform as WiFi Street Coverage Explorer (WiFiStreetCoverageExplorer).

The remainder of this paper is organized as follows. In Section 2 we introduce related work, then in Section 3 we present our framework. An analysis of the results that can be visualized and quantified by our framework is given in Section 4 for the city of Turin. Finally in Section 5 we conclude the paper.

2 Related Work

Knowledge of the characteristics and the distribution of wireless networks is of fundamental importance for a number of related applications that can exploit this information to provide additional services to their users. For example, WiFi APs position is used by location-based services to identify the position of the user in alternative to the GPS signal, and WiFi coverage is used by ISPs to offer connectivity on the go to their residential DSL subscribers. Thus, several measurement and characterization studies of urban wireless networks are present in the literature both for the case of WiFi and Cellular technologies.

Estimation of location and coverage areas of base stations is addressed in Neidhardt et al. (2013) for the case of crowdsourced measurements, that are the common scenario in these studies because ISPs and mobile operators do not share their databases with the community. Furthermore such databases only contain the addresses of the households of users and, thus, are not very precise for AP localization purposes. The authors compare different position estimation algorithms and highlight the need for further research in the field of coverage area estimation. In Zhang et al. (2011) the authors highlight that a great amount (35+) of measurements is needed to triangulate precisely the position of a WiFi hotspot, so we decided not to try triangularization, but to stick with raw WiFi measures accomplished by roaming crowdsourcing users.

Given the data collected by smartphones in Lausanne, the distribution of WiFi APs in the city is analyzed in Berezin et al. (2012), showing that WiFi coverage is quite large and that this infrastructure, even if unplanned and unmanaged, is able to provide high data rates at almost no deployment cost.

A specific application scenario is considered in Castignani et al. (2012), the authors analyze the performance of community networks in France measuring throughput efficiency for cellular data offloading through WiFi network.

The interest in the exploitation of the WiFi infrastructure has also fostered the creation of several online services that allow users to locate APs positions or smartphone measurements on a map, together with the strength of the signal identified. The most advanced solutions are community based websites such as WiGle (WiGLe), OpenSignal (OpenSignal), OpenBMap (OpenBMap), OpenWLANMap (OpenWLANMap), that are based on crowdsourced measurements.

The potentiality of such infrastructure is also leveraged directly by some company that allows its subscribers to access the Internet through their WiFi hotspots spread around the world. Interactive visualizations of the possible coverage are provided by online maps showing the position of their WiFi routers (e.g., Vodafone (VodafoneWifiCommunity), Orange (OrangeHotspots), FON (FON), etc.).

However, online maps that show the location or coverage of WiFi hotspots do not exploit the map semantics to provide further information. In fact, the map is used just as an image on top of which they draw a point, the AP location, or a colored area, the AP coverage. No information on the coverage area underlying topology is used, for example, to know if that area comprises schools, malls, parks, streets, etc.

In this paper we present how WiFi measurements may benefit from OSM geospatial information to characterize the type of coverage provided. In this specific case we use OSM data to define how much of a given street is covered by the WiFi network. This gives much more insights to anyone that wants to leverage on such infrastructure, than the raw information on the density of APs in a given area or on the area coverage (that may comprise inaccessible locations such as private buildings).

In this paper we provide, to the best of our knowledge, the first study on the effective street coverage of WiFi deployments in an urban scenario. Moreover, we have also developed an open source framework to extract, measure and visualize such information given geolocated WiFi signal measurements. The framework is available as open source software on Github (WiFiStreetCoverageExplorer).

3 The Framework

In this section we present the framework used to characterize and analyze real urban environments in terms of number of APs deployed, their density and their coverage areas.

3.1 Dataset

The framework has been applied both on measurements we collected with an ad hoc smartphone application and on a dataset retrieved from one of the open databases available online.

In a first experiment, we used the measurements collected with a smartphone application we developed, called PheromoneWiFiStreet. This application performs geo-localization and network scanning using the smartphone WiFi interface. When activated, the application performs a scan every 60 seconds and logs location and network information, such as SSID, signal strength, longitude, latitude, etc., on a database in the cloud. The application was deployed for a few months on the smartphones of a small group of users, in order to collect WiFi sensing data while in mobility within the city of Turin. This activity resulted in the collection of a small dataset (250,000 measures from May 2014 to May 2015) that, nonetheless, highlighted the potential of a “WiFi coverage”-based connectivity service for on-street IoT devices within the smart city.

The format of the data that can be used as input is described in Table 1. Each measurement is defined by the position: latitude, longitude, and height (m), the timestamp (s), the BSSID and SSID of the sensed WiFi network, its Capabilities, the operating WiFi channel (Frequency (MHz)), the signal strength (RSSI (dB)), the model of the smartphone used for sensing the WiFi network (Phone model), and the provider (Loc Provider) and the accuracy (Loc Accuracy) of the location of the measuring smartphone, as reported by the Android OS at the moment of the measurement.

Table 1. The format of the result of the scan of a single WiFi network that was sensed by the Android application.

Field	Sample value	Notes
coords	[7.684115, 45.079621]	[longitude, latitude]
height	0	In meters
timestamp	1458213700143	Epoch-based
BSSID	d0:d4:12:xx:yy:zz	MAC address of the WiFi hotspot
SSID	Alice-12345678	The WiFI network name as seen from

		the connecting device GUI
Capabilities	[WPA-PSK-CCMP+TKIP] [WPA2-PSK-CCMP+TKIP] [WPS][ESS]	For example, supported security protocols (WEP, WPA, …)
Frequency	2412	WiFi channel (in MHz)
Level	-96	RSSI (Received Signal Strength Indicator) in dB
Phone model	E2363	Model of the smartphone that is scanning for WiFis
Loc Provider	fused	Android location provider (fused, gps, network, wifi)
Loc Accuracy	14.142	In meters

In order to estimate the coverage of the APs sensed by the crowdsourcing app, we experimentally measured in various urban on-street scenarios the function mapping from the Received (by a smartphone S) Signal Strength, in dB, to the distance between S and the in-home AP as in Table 2. From this table we can assume that the coverage of a given AP extends for 50 m (dmax in Figure 1) from the AP's location. Such a maximum range is compatible also with the assumptions in (Berezin et al. 2012, Lee et al. 2010).

Table 2. Mapping from the smartphone Received Signal Strength to the distance between the smartphone and the AP

Mean RSSI (dB)	Distance from AP (m)
-33	0
-64	10
-73	20
-75	30
-83	40
-90	50

When a measuring smartphone S reports the sensing of an AP in a certain point P in space with a signal strength of, let's say, -73 dB, we look at Table 2 and discover that the AP is located at 20 meters from P (d in Figure 1), but we do not know in which direction the AP is located (we are not triangulating multiple measures to find the AP location, see Zhang et al. (2011)). In any case, whatever the direction, a circle of diameter dmax - d (50 m - 20 m = 30 m) may be drawn around P and the WiFi coverage of the AP is guaranteed to be present in that circle (the greater dashed circle in Figure 1). By repeating the same task for every measure made by every smartphone in our experiment we estimated the WiFi coverage of home APs on the city streets.

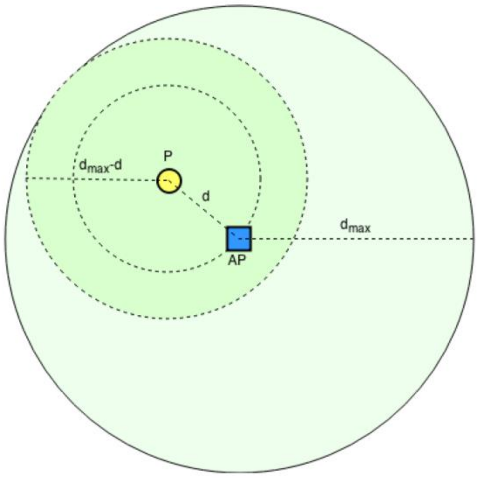

Figure 1: Our (conservative) approach to estimating the available coverage of an AP around a measure point P, where the AP has been sensed by a measuring smartphone.

In a second test, in order to address the scarcity of measures that we were able to obtain with the recruitment of just a small group of people for crowdsourcing WiFi measures, we downloaded the measurements from WiGLE (Wireless Geographic Logging Engine), through their API (WigleApi). WiGLE has collected more than 200 millions WiFis since 2001 and has the most extensive accessible collection of WiFi data, to the best of our knowledge. We also tried other WiFi data providers, like Open WLAN Map (OpenWlanMap), but their coverage, at the time of writing, is far less dense than WiGLE's.

In the case of the data imported into our database from WiGLE, no signal strength information is provided as only the estimated AP location is given by WiGLE, along with the WiFi network MAC address and SSID name. WiGLE estimates the position of an AP by triangulating all the measures regarding the AP made by WiGLE users. When importing WiGLE data we had to "adjust" them to our format, which requires the indication of a signal strength in order to estimate a coverage for the sensed WiFi network. In order to cope with this problem, we assumed a signal strength of -20 dB for every WiFi network returned by WiGLE. Such signal strength is the strength typically measured by a smartphone, if positioned in the near proximity of a typical home WiFi AP (as from our experimental evaluation). Such assumed signal strength directly translates to a coverage of 50 m all around the AP.

Figure 2 shows the resulting map of the AP locations retrieved from WiGLe for year 2015 and their coverage range in the city of Turin.

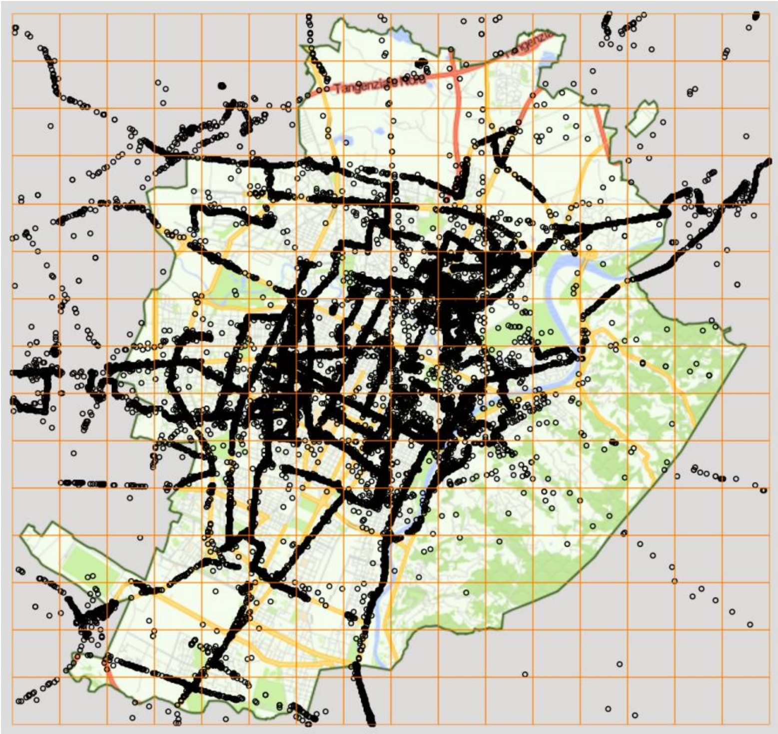

Figure 2: Map of the AP locations in the city of Turin retrieved from WiGLe for year 2015.

3.2 OSM Integration

Our application is designed to estimate the coverage that in-house WiFis can deliver to on-street IoT smart objects, like dumpsters, traffic lights, and manholes. In order to do this, beyond obtaining a dataset of hotspot WiFi locations for the city of Turin, we leveraged the OpenStreetMap initiative (OpenStreetMap). OpenStreetMap aims at building a map of the entire world via crowdsourcing. The OpenStreetMap database contains a lot of semantically rich data about the world: of course, it contains information about the streets of cities, their name, and their carriageways.

By mapping the coverage circle of each WiFi of the obtained dataset onto the streets of Turin, we managed to calculate the level of WiFi connectivity to be expected on each "10 m segment" of every street of the city. We had to make some assumptions, though:

1. we took for granted the WiFi AP locations returned by WiGLE, even though a noticeable number of APs seem to be located on the streets and not within buildings; this may be due to the fact that the majority of WiGLE users providing WiFi scans to the server do that while moving along the city roadways, so that triangulation for determining the exact AP location becomes difficult even if many measures are available for the AP;

2. we assumed that each WiFi AP has a coverage area spanning a circle of 50 m radius around it: this is a common rule of thumb assumed in many works concerning WiFi coverage (Berezin et al. 2012, Lee et al. 2010), furthermore we experimentally validated the 50 m rule with a small set of independent measures;

3. it was assumed that WiFi APs are kept always on by their owners, whereas this may not be the case (for example, people may want to turn off their APs when they do not use them in order to reduce electromagnetic emissions or to save electric power);

4. we assumed that an AP sensed once during our period of observation is always available: in reality an AP may be turned off because its owner decides to discontinue the DSL subscription, for example.

The resulting web application, named "Wi-Fi Street Coverage Explorer" (WiFiStreetCoverageExplorer), is capable of showing which parts of the city streets are covered by WiFis and, thus, may be the target for the deployment of smart objects needing Internet connectivity. The provided visualization, as shown in Figure 3, may be customized by selecting the area of interest within the city, the period of time that one wants to investigate, and, optionally, by setting filters on the accuracy of the location of measures and on the SSID. By using the SSID filter in combination with regular expressions one may understand the WiFi coverage in the area of interest from the point of view of a single ISP operator; in fact, operators usually adopt a simply identifiable naming convention when assigning default names to the SSIDs of the WiFi networks owned by their users (for example TIM's WiFi are named like Alice-xxxxxxxx, Telecom-xxxxxxxx, or TIM-xxxxxxxx).

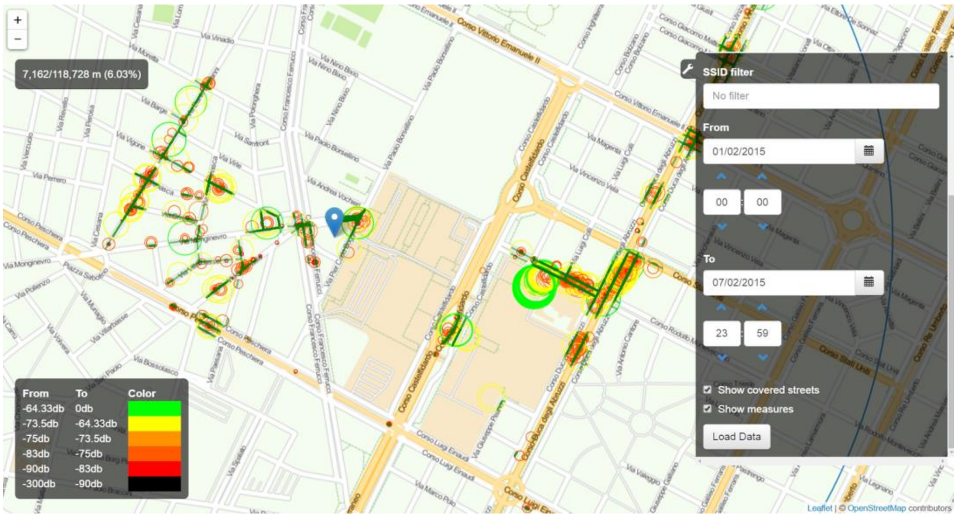

Figure 3: Web User Interface of the Wi-Fi Street Coverage Explorer.

The Wi-Fi Street Coverage Explorer software architecture is shown in Figure 4. The application is built using the Leaflet Javascript mapping library (Leaflet), displaying OSM customized tiles, and an instance of a MEAN stack. Here MEAN means Mongo-Express-Angular-Node; in fact, our solution makes use of an AngularJS browser client, talking to a NodeJS server backend. The Node backend uses the Express web framework in order to expose APIs capable of collecting WiFi scans and of answering to user queries. Finally, a Mongo database is used as data storage.

The Mongo DB contains both the raw WiFi measures and a set of ad-hoc, periodically updated, aggregations, in order to efficiently respond to user queries regarding the city streets and their WiFi coverage.

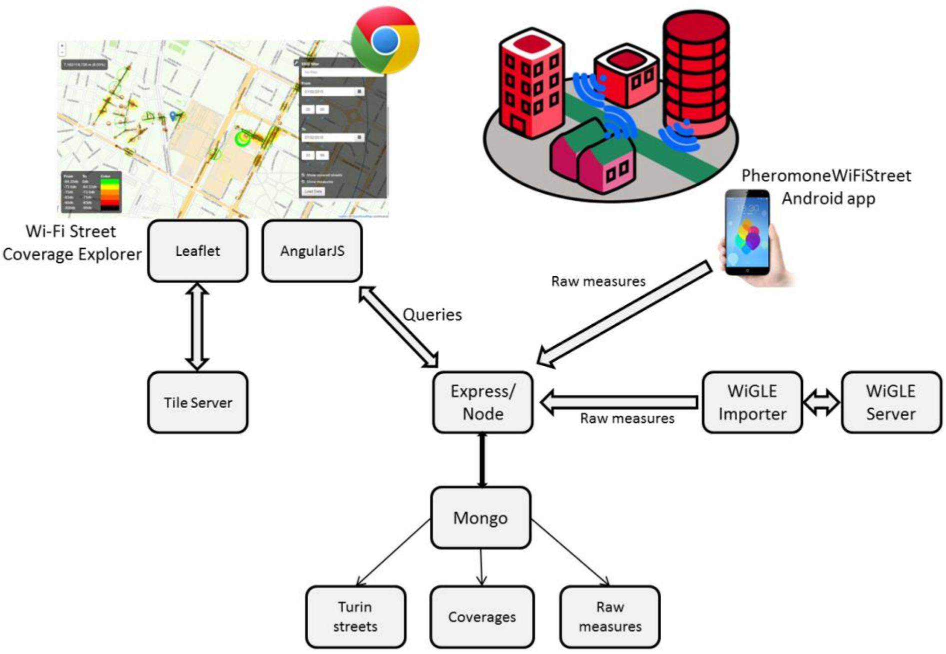

Figure 4: Software architecture of the WiFi Street Coverage Explorer.

4 Case Study

We collected a first set of measurements with two campaigns that made use of a specific Android application named PheromoneWiFiStreet, as described in Section 3. However, those campaigns were limited to a very small area of the city and they did not collect enough information to characterize the variations of the urban WiFi scenario in different locations of the city.

Thus, the results presented in the following part of the paper are based on another set of measurements that we retrieved from the WiGLe public dataset (WigleApi) in order to extend our initial analysis to a wider area and a larger number of measurements. In addition this experiment proves the ability of the system to import and process information from external databases using the format previously described in Table 1.

4.1 The dataset of the city of Turin

To analyze the detail of the WiFi coverage in different locations of the city, we divided the city of Turin, about 15 kilometers long and 16 kilometers wide, into a series of non-overlapping blocks. For each block we provide a statistic on the density of the APs and a study of how those APs are able to cover the area inside a block, and in particular the streets within it. In fact, the novelty of our framework is that its focus is to relate WiFi coverage with map information, in particular using the resources available from OpenStreetMap. Results are computed for two block sizes: 1 kilometer (a 15x16 grid) and 500 meters (a 30x32 grid).

4.2 AP density

The first result extracted from the dataset is the number of unique APs in each block of the city. This result gives a first, rough, estimation of the WiFi coverage ratio we can expect in each area. However, in this case, we do not take into account many factors that can influence the effective coverage such as the number of times, and locations, a certain AP has been identified, in which position it is placed and how strong it the strength of its signal is.

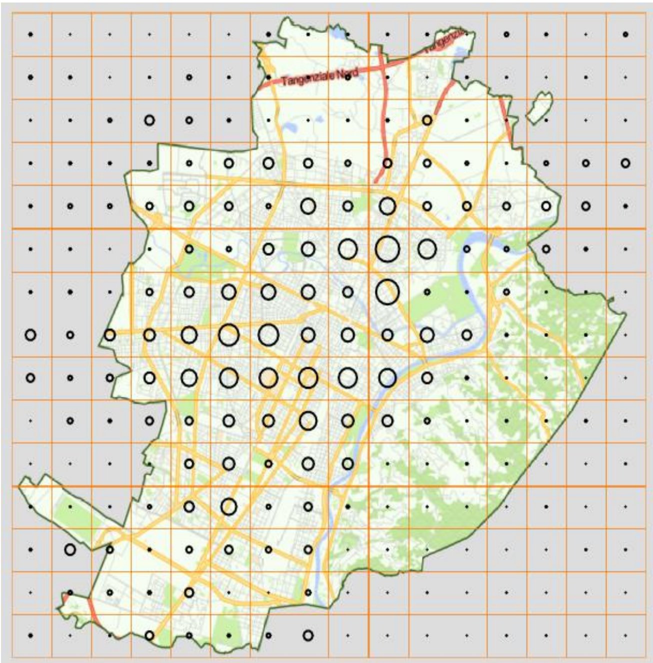

Figure 5: Map of the city of Turin with 1km x 1km blocks, circle size represents the number of AP measured in each block.

Figure 5 shows a graphical representation of the AP density computed on the city of Turin for a grid of 1km x 1km blocks. Here the number of unique APs (identified by the MAC address) measured in each block during a year is represented by the size of a circle placed in the centre of the box, the bigger the circle the greater the number of APs. As expected the highest number of APs per block is concentrated in the city center (row 7, columns from 6 to 10) where the largest circles represent around a thousand of APs. We refer to the blocks using their row and column number starting from 1,1 for the block in the lower left corner.

However, as already pointed out in Jones & Liu (2007), because the data is collected by a fleet of drivers (or walkers) that travel around the city without a precise plan, major roads are traveled more often than minor roads. Thus, when this data is used to calculate the location of the APs, it is common that the “weight” of the major roads unfairly influences the discovery of the APs. They refer to this effect as “arterial bias” and we notice that blocks that are crossed by a major road present a higher number of APs with respect to the adjacent ones (e.g. blocks 10,9, 10,10 and 10,11 in the northern part of the city).

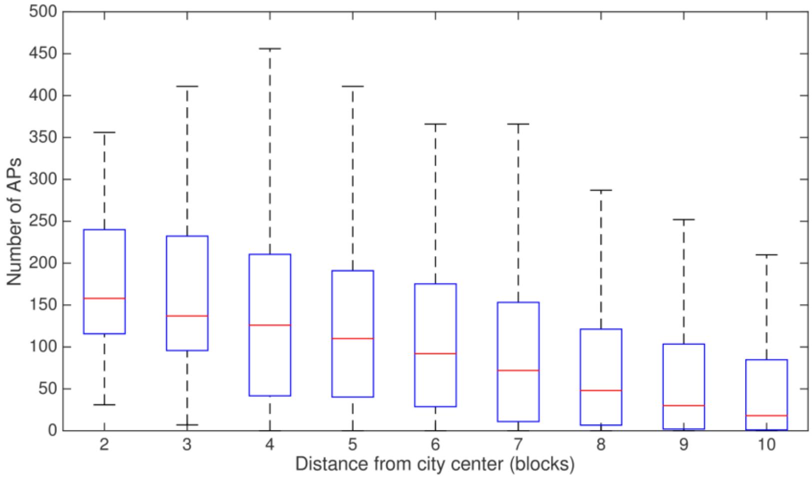

Figure 6: Boxplot of distribution of APs per block considering different areas around the city center of Turin.

Figure 6 shows the statistic of the number of APs per block if we consider a block size of 500m x 500m. In the boxplots we notice that the more we extend the analysis region from the city center (block 14,15) the more the distribution of density of the APs decreases. If we consider only the 5x5 grid with maximum distance from the city center of 2 blocks (shown in Figure 7 with the black box), the median number of APs per block is 158, then it decreases and it reaches 18 if the region that we consider is 21x21 grid with all the blocks less than 10 blocks apart from the city center. We limit this study to the central region of the city because we rely on crowdsourced measurements and the more we move away from the most populated area, the less measurement we have, and the less accurate the estimate of the real AP density is (as we can see from the numerous blocks with few APs at the edge of the city in Figure 5).

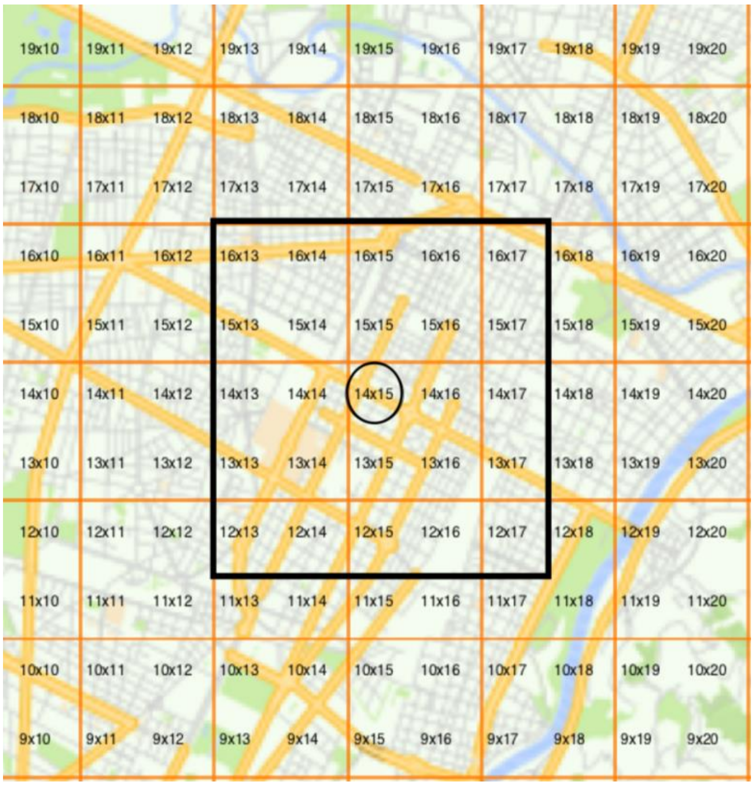

Figure 7: Map of the analysis grids of increasing size, centered on the city center (cell 14,15), that are used to characterize the AP deployment in the city. The black box represents the 5x5 grid with blocks with a distance from the city center of two or less b

4.3 AP coverage

The second analysis performed on the WiFi dataset is the computation of the portion of each block covered by WiFi. In this case we take into account both the position of the AP and its signal strength, so we can identify the area, within a given range from the AP, that is covered by its signal.

We know that there are many factors that can interfere with WiFi signal propagation, but our focus is more on exploiting map information than on precise estimate of WiFi coverage, so we resolve to use common ranges for indoor APs that are estimated between 20 and 50 meters as in Berezin et al. (2012).

Figure 8: Access points position and coverage as retrieved from the WiGle dataset (year 2015) for a 500m x 500m block with coordinates 14,12. AP coverage radius is set to 25 meters.

In Figure 8 we show the WiFi coverage resulting from the WiGle dataset for a 500m x 500m block. The circles represent the position and coverage of the 154 APs identified in this area. The unmanaged deployment of the APs is responsible of the inefficient coverage of the area within the block because there is a great overlap between nearby APs.

Clearly, the information on the amount of the block area covered by WiFi connectivity is a good result to evaluate the diffusion and the deployment of WiFi community networks. However many of the services the network can provide will be used from public areas, for example streets. Thus, a more interesting result, that we present in this section, is the amount of streets covered by the WiFi network.

The computation of the portion of the streets in each block that is covered by WiFi can be obtained because our framework uses both the information on the APs position from the WiGle dataset and the information on the underlying map retrieved from OpenStreetMap. Figure 8 shows the portion of the streets within the APs coverage area as a black line. As described in detail in Section 3 we compute the WiFi connectivity of the streets considering non-overlapping streets segments of 10 meters, so it may happen that the portion of the street marked as covered in the map extends a little bit outside the circles. As expected, main streets have a higher percentage of APs because they have been measured (and traveled) more frequently. However, also the side streets show a good WiFi connectivity. For this block our framework reveals an area coverage of 50% and a street coverage of 60%, a little bit higher as can be foreseen from the figure. Street coverage is defined as the ratio between the total length of the streets in a block and the sum of the portions of the streets inside the AP coverage circles.

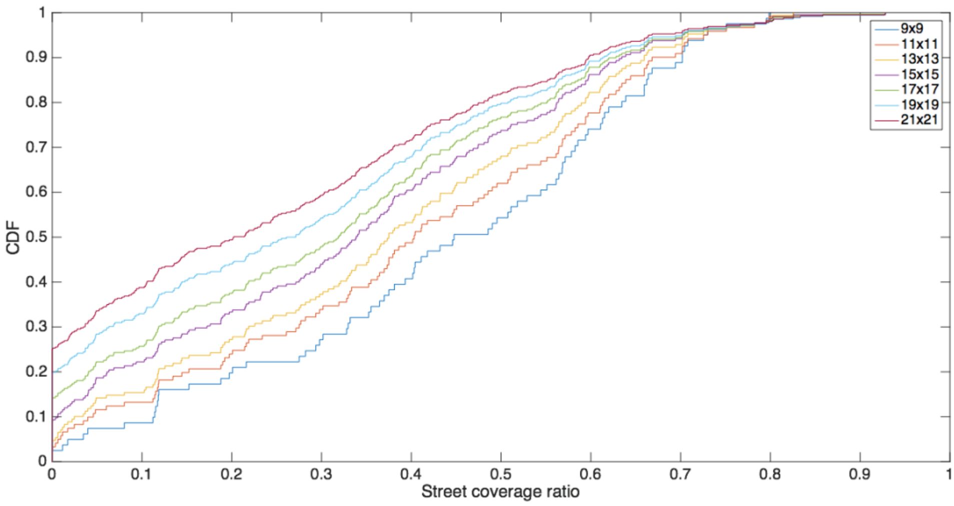

Figure 9. Street coverage ratio cumulative distribution considering square grids of blocks of increasing size around the city center.

Figure 9 shows the street coverage ratio distribution around the city center considering square grids of increasing size. The smallest one (9x9) comprises all the blocks with distance (in blocks) less than or equal to 4 in all the directions. We can observe that the median street coverage ratio close to the city center is around 50% and decreases as much as we include blocks far from it.

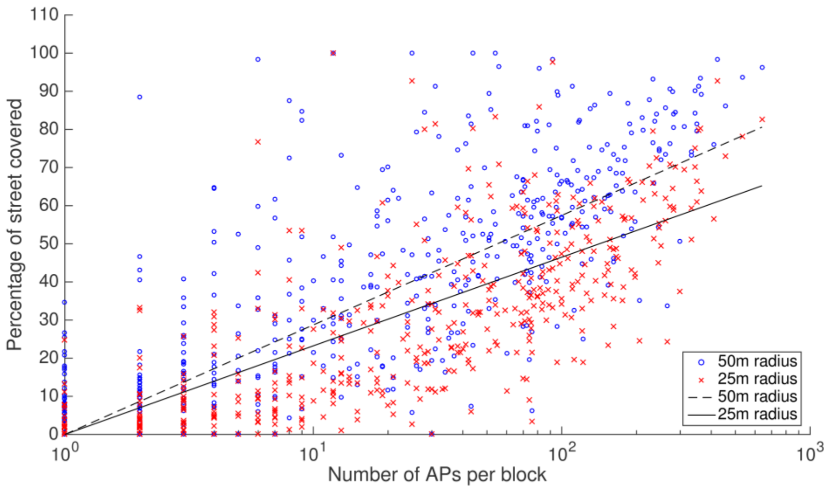

Figure 10. Percentage of street in a block (500m x 500m) that is covered by WiFi versus the number of APs measured in the block.

In order to evaluate the AP density impact on the street coverage percentage, we have plotted the relation between these values in Figure 10 for each block of 500m x 500m. The circles represent the estimate of the AP coverage with a radius of 50m and the crosses the AP coverage with a radius of 25m. The distribution of the points shows a relatively small difference between the two estimates. Fitting the data with a linear regression model reveals that the assumption of a 50m radius gives a street coverage ratio that is 1.23 times better than the ratio given by assuming a 25m radius. This analysis shows that in the case of an unplanned deployment of WiFi access points, the coverage of the surrounding streets increases in a logarithmic fashion. Thus, it is relatively easy to achieve around 50% of street coverage in a block, i.e., a hundred APs may be sufficient, but a great increase above that percentage may be impractical, i.e., we need about a thousand of APs to reach 70-80%. In this second case, an intelligent choice of the placement of a few new APs may, instead, be a viable option to a significant increase of the overall street coverage.

5 Conclusions

In this paper, we have presented a unique framework for mapping wireless measurements on OpenStreetMap data that we release as open source software on Github, named WiFi Street Coverage Explorer (WiFiStreetCoverageExplorer). Given the GPS coordinates, SSID (and eventually the MAC address) of WiFi access points, we augment the common practice of representing this data on a map with the ability to relate it with other geographical information. The possibilities that this tool offers are endless. In this specific case we have shown the results of mapping a WiFi dataset retrieved from the WiGle website on the street information of the city of Turin. At first, we have characterized the different areas of the city computing a common result for this kind of analysis, that is the access point density. Then, we have extended this initial result matching the position and coverage range of the hotspots with the street map of the city and computing the percentage of streets with WiFi connectivity in each area. This study is of particular interest both for the increasing number of WiFi Community Networks and for the upcoming Internet of Things smart city objects, like dumpsters, traffic lights and manholes. In fact, these devices access those networks from streets and public places, so there is more interest on the WiFi street coverage ratio than on the more publicized hotspot density.

Future work will focus on three tasks. First on improving the system with more reliable AP information from direct measurements or other open dataset because the results obtained with the WiGle data does not seem to reflect so accurately the real deployment and position of the wireless hotspots. Second on extending the results that can be computed by the system, for example, adding the information on the connectivity gap distribution along the streets. Third on studying the optimal placement of the minimal amount of hotspots in the city, so that the WiFi street coverage can reach the desired level of service.

References

Berezin, M.E., Rousseau, F. & Duda, A, (2012), Citywide mobile Internet access using dense urban WiFi coverage, in ‘Proceedings of the first workshop on Urban networking (Nice, 10-13 December, 2012)’, pp. 31-36

Castignani, G., Blanc, A., Lampropulos, A. & Montavont, N. (2012), Urban 802.11 Community Networks for Mobile Users: Current Deployments and Prospectives, ‘Mobile Networks and Applications’, 17.6, 796-807

FON (Last checked 2016), “The Global WiFi Network providing WiFi access through hotspots”. URL: https://fon.com/

Jones, K., & Liu, L. (2007). What where wi: An analysis of millions of wi-fi access points, in ‘Proceedings of the International Conference on Portable Information Devices (Orlando, 25-29 May), pp. 1-4.

Leaflet (Last checked 2016), “Leaflet – an open-source Javascript library for mobile-friendly interactive maps’, URL: http://leafletjs.com/

Lee, K., Lee, J., Yi, Y., Rhee, I., & Chong, S. (2010). Mobile data offloading: how much can WiFi deliver?, IEEE/ACM Transactions on Networking, 21.2, pp. 536-550

Neidhardt, E., Uzun, A., Bareth, U. & Küpper, A.(2013), Estimating locations and coverage areas of mobile network cells based on crowdsourced data, in ‘Proceedings of 6th Joint IFIP Wireless and Mobile Networking Conference (Dubai, 23-25 April 2013)’, pp. 1-8

OpenBMap (Last checked 2016), “OpenBMap.org a free and open map of wireless communicating objects”, URL: http://www.openbmap.org/

OpenSignal (Last checked 2016), “OpenSignal: 3G and 4G LTE Cell Coverage Map”, URL: http://opensignal.com/

OpenStreetMap (Last checked 2016), “Open Street Map”, URL: https://www.openstreetmap.org

OpenWLANMap (Last checked 2016), “Open WLAN Map - free and open WLAN-based location services”, URL: http://www.openwlanmap.org/

OrangeHotspots (Last checked 2016), “La couverture des hotspots wifi d’Orange”, URL: http://reseaux.orange.fr/carte-hotspots

SkypeWifi (Last checked 2016), “Skype Wifi”, URL: http://www.skype.com/en/features/skype-wifi/

VodafoneWifiCommunity (Last checked 2016), “Vodafone Wi-Fi Community”, URL: https://wificommunity.vodafone.it/

WiFiHaLow (Last checked 2016), “Wi-Fi HaLow”, URL: http://www.wi-fi.org/discover-wi-fi/wi-fi-halow

WiFiStreetCoverageExplorer (Last checked 2016), “WiFi Street Coverage Explorer”, URL: (the link to this content, that contains non anonymous information, will be provided after the double blind review process)

WiFiTastic (Last checked 2016), “WifiTastic is the easiest, cheapest way to set up a secure commercial Wifi Hotspot”, URL: http://www.wifitastic.com/

WiGLe (Last checked 2016), “WiGLe.net. All the networks. Found by Everyone”, URL: https://wigle.net/

WiGLeApi (Last checked 2016), “WiGLe Web API”, URL: https://wigle.net/wiki/index.cgi?API

Zhang, Z., Zhou, X., Zhang, W., Zhang, Y., Wang, G., Zhao, B. Y., & Zheng, H. (2011). I am the antenna: accurate outdoor AP location using smartphones, in ‘Proceedings of the 17th annual international conference on Mobile computing and networking (Las Vegas, 19-23 September)’, pp. 109-120.