How much can we trust RSSI for the IoT indoor location-based services?

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***Abstract*— One of the key challenges in the ever-changing ubiquitous computing environment of Internet of Things is accurate determination of each of its' elements location. Indoor localization for smartphones has been in line with this research initiatives in the last decade, along with the inherited background from wireless sensor networks perspective. Therefore, most of the algorithms from the literature are based on distance measurements obtained from radio signal strength ranging technique and evaluated mostly through simulations. In this paper, we experimentally evaluated a well-known technique for localization based on multidimensional scaling, using different models of smartphones. Additionally, we analyzed the behavior of the signal strength measured by the smartphones under different field condition. From our results, we concluded that radio signal strength indicator should be combined with more accurate ranging techniques into hybrid solutions to be used for indoor localization of smartphones.**

Keywords—indoor localization; smartphone; experimental evaluation; RSSI

I. INTRODUCTION

In the recent years, the concept of scattered devices dedicated to one-purpose application has been replaced with the Internet of Things (IoT) and machine-to-machine (M2M) communication for general-purpose applications [1]. One of the most important services of the IoT is localization, i.e. the process of discovering the location of the objects that participate in the IoT network. While solutions for outdoor localization generally provide reliable and satisfactory results, indoor localization is still a demanding problem. Localization accuracy is a key issue for location-based services [2][3]. This applies especially for smart buildings, inseparable part of smart city, where the need for new approaches with higher localization accuracy is demanding.

The area of indoor localization has grown fast in the last decade, mostly due to the advances in smartphone industry and the introduction of many new sensors and smartphone features. Since the widely used satellite positioning systems, like GPS or Galileo, are almost useless in indoor environment, many different approaches for indoor localization have been proposed during the last years [4][5][6]. Algorithms for localization can be divided into two groups, based on proximity, and based on distance. The first group considers only the information about the proximity to other nodes in the network, while the second considers the distances between the nodes. For inter-node distance measurements, different ranging techniques can be used, like Radio Signal Strength Indicator (RSSI), Angle of Arrival (AoA), Time of Arrival (ToA) or Time Difference of Arrival (TDoA). Among them, RSSI is the most explored technique since it does not require any additional hardware.

Localization algorithms from the literature based on RSSI are evaluated mostly through simulations, where RSSI biased with noise is modeled with normal or uniform distribution in the simulation scenarios [7]. The aim of this paper is to experimentally evaluate a well-known localization technique from the literature based on multidimensional scaling (MDS) algorithm, i.e. to investigate weather smartphone localization can rely exclusively on RSSI. We have chosen MDS because it is one of the most explored and the most accurate techniques for localization [6][7]. Still, there is a lack of experimental evaluation of MDS, especially in smartphone domain. To the best of our knowledge, this is the first research that experimentally evaluates the accuracy of MDS for indoor localization of smartphones. Therefore, in the first part of our research, we collected RSSI measurements from different smartphone models under field conditions, and without additional processing, we used these measurements for localization, just as we expect a real positioning application would behave. In the second part of our research, we analyzed how RSSI is influenced by other surrounding objects. We used the same smartphones and collected new RSSI measurements in environment with and without communication devices that can influence the RSSI, like WiFi or physical obstacles.

Localization accuracy obtained in our experiment differs greatly from the results obtained in simulation scenarios for the same localization algorithm, i.e. the localization accuracy is incomparably worse under field conditions. On the other side, the second experiment confirmed that averaging repeated RSSI measurements in "ideal" environment (without interference from other devices) gives expected log-like curve of RSSI versus distance. Despite that, introducing the obstacles makes RSSI unreliable measure of distance. Therefore, we suggested that RSSI should be used as a base for coarse grained localization, but additional information should be necessary for fine grained localization.

The rest of this paper is organized as follows. The next section describes our first experimental setting and the process of collecting smartphone RSSI under field condition, as well as the results obtained when localization algorithm was applied to our measurements. Section three presents our second experiment, i.e. collecting RSSI measurements influenced by WiFi device or physical obstacle. Section four discusses and summarizes our findings. The paper is concluded in section five.

II. Localization Accuracy under Filed Condition

In this section, we are going to explain in detail the localization process under field condition.

A. Collecting RSSI measurements

In our first measurement set, 6 different smartphone devices were used, as given in Table I, deployed in a room measuring *8m* x *7m*, in 5 different ways (configurations). One such configuration is shown in Fig. 1. The distances between the devices in all configurations varied from 1m to 8m.

TABLE I. SMARTPHONE MODELS AND CORRESPONDING FCC IDS

Device	Device	FCC ID
D1	HTC Legend	NM8-PB76110
D2	Samsung Galaxy S4	A3L-GTI9505
D3	Samsung Galaxy S3	A3L-GTI9300
D4	Samsung Galaxy S4	A3L-GTI9505
D5	Samsung Galaxy S4	A3L-GTI9505
D6	Samsung Galaxy S4	A3L-GTI9505

For each pair of devices, we conducted four measurements, i.e. if we want to measure the RSSI between D1 and D2, we recorded two D1 measurement toward D2 and two D2 measurement toward D1. Therefore, 300 measurements were collected in total, i.e. 30 measurements for each configuration, repeated twice.

Inside the room, there were two active WiFi Access Points (APs), which may had affected the RSSI measurements. In order to simulate a real case scenario, we did not turn the WiFi devices off, since we expect that WiFi APs, along with other communication sources, are generally present in many real-life indoor environments. Solutions for indoor positioning should be robust enough to minimize the effect of different communication devices (WiFi, modems, Bluetooth) on the accuracy, since their presence cannot be anticipated and avoided.

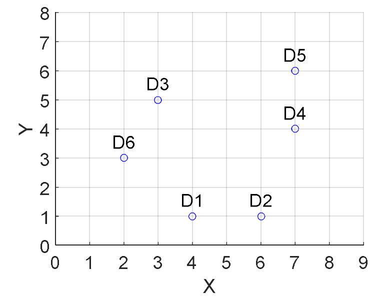

Fig. 1. Example of one deployment of the smarthphones

B. Translating RSSI into distance

Most of the algorithms for localization are based on distances between the peers. Therefore, each RSSI measurement needs to be translated into distance, which is the most challenging part of the localization pipeline.

The RSSI measurements are given in dBm, which stands for decibel milliwatt. The relationship between a power given in watt and a power given in decibel milliwatt is given in (1).

$$RSSI = 10log_{10}\frac{P}{1mW}\ [dBm] \quad (1)$$

The relationship between the power and the distance is given in (2) and (3),

$$A_d = -A_1 - 10nlog_{10}d \quad (2)$$

$$d = 10^{\frac{-A_1-A_d}{10n}} \quad (3)$$

where A_d is the RSSI value measured at distance d, A_1 is the power measured at distance of 1m, while n is a constant obtained empirically.

Different smartphones have different values for A_1, but they are not provided by the vendors. One way to obtain those values is from the measurements provided by the Federal Communications Commission (FCC), publicly available at [8]. Applying those values to a general solution requires frequently updates because new smartphone models appear every day, thus adding additional complexity to the localization algorithm, which otherwise is expected to be lightweight and to operate in real time.

Therefore, we obtained the constant values for n and A_1 (4), by applying a modified Newton method based upon the model trust region approach [9], as shown on Fig. 2.

$$d = 10^{\frac{56.02-RS}{176.3}} \quad (4)$$

C. Applying localization algorithm

In this paper, we used our measurement set to evaluate localization accuracy. A well-known technique from the literature known as Multidimensional scaling (MDS) was employed [10]. MDS algorithm uses the distances between each pair of object as an input and generates two dimensional (2D) points or three dimensional (3D) points as an output.

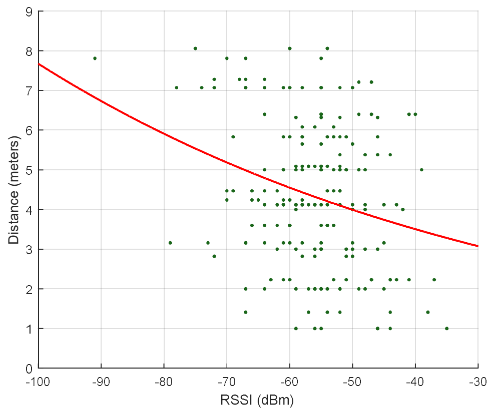

Fig. 2. Relationship between RSSI values and distances

Multidimensional scaling as a technique for Wireless Sensor Networks (WSNs) localization consists of the following three steps [10]:

- Step 1: Calculate the distances between every pair of nodes and generate a distance matrix that serves as an input to the step 2.
- Step 2: Apply multidimensional scaling to the distance matrix. The first largest eigenvalues and eigenvectors give a relative map with relative location for each node.
- Step 3: Transform the relative map into absolute map using sufficient number of anchor nodes.

Along with the high accuracy reported in the literature for different network topologies (2D, 3D and 3D surface networks) for small number of anchors placed random, MDS has other benefits, such as stability under large range error measurements [11][12]. Namely, in most simulations from the literature, the radio range measurement error is modeled with uniform (or normal) distribution. MDS performs well even for range measurement error up to 50% of the radio range.

D. *Analyses of the localization accuracy*

As evaluation metric, we used the localization error, which is the difference between the real and the predicted position. For WSN that consists of W unknown nodes, where (x_i, y_i, z_i) is the real position and (x_i', y_i', z_i') is the predicted position of i-th node, the average localization error (ALE) can be expressed as in (5).

$$ALE = \frac{1}{W}\sum_{i=1}^{W}\sqrt{(x_i - x_i')^2 + (y_i - y_i')^2 + (z_i - z_i')^2} \quad (5)$$

In our experimental setup, we provided dense 3D network with large fraction of anchors, and evenly deployed smartphones. This configuration, in case of simulation, would have achieved localization error of up to few centimeters. However, besides all abovementioned preconditions, the results we obtained significantly differ from the results reported in the literature, and range from 0.38m to 7.78m (Table II).

Visual interpretation of the results can be seen in Fig. 3.

III. ENVIRONMENTAL INFLUENCE TOWARD ACCURATE RSSI

A. *Set up of the experiment*

To further explore how people and devices affect the RSSI between two measuring devices, we set up an additional experiment. The RSSI from two mobile devices (smartphones) was measured at distances of 1, 2, 4 and 8 meters in different scenarios in the area without (or with very low) influence from other WiFi devices. We considered three scenarios: without obstacles around, with one obstacle (person) around and with two obstacles (persons) around. For each scenario, we have measured signals for different operation modes in which the obstacle/person could be. We measured signals when person (or two persons) represented only obstacle (without additional devices), when person was Access point (by turning on Hot spot mode on her Smartphone) or when person was having phone conversation. Every measurement was repeated four times: RSSI from Device 1 to Device 2 and vice versa, resulting with the total of 1264 measurements.

TABLE II. LOCALIZATION ERROR OBTAINED FOR MDS-BASED LOCALIZATION TECHNIQUE

Test scenario	**1**		**2**		**3**		**4**		**5**	
#measurement	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
empty values	1	3	0	0	0	0	0	1	0	0
Average localization error (%R)										
mean	39	32	39	50	35	20	39	39	108	108
variance	360	528	53	696	117	150	181	374	1055	778
min	6	5	29	27	18	8	26	21	61	72
max	71	69	51	107	48	46	67	77	148	147
Average localization error [m]										
mean	2.78	2.33	2.84	3.67	2.06	1.16	3.13	3.15	3.41	3.42
variance	1.88	2.75	0.28	3.69	0.4	0.51	1.18	2.43	1.06	0.78
min	0.43	0.38	2.1	1.96	1.06	0.48	2.12	1.67	1.93	2.26
max	5.11	4.95	3.72	7.78	2.82	2.69	5.37	6.2	4.69	4.65

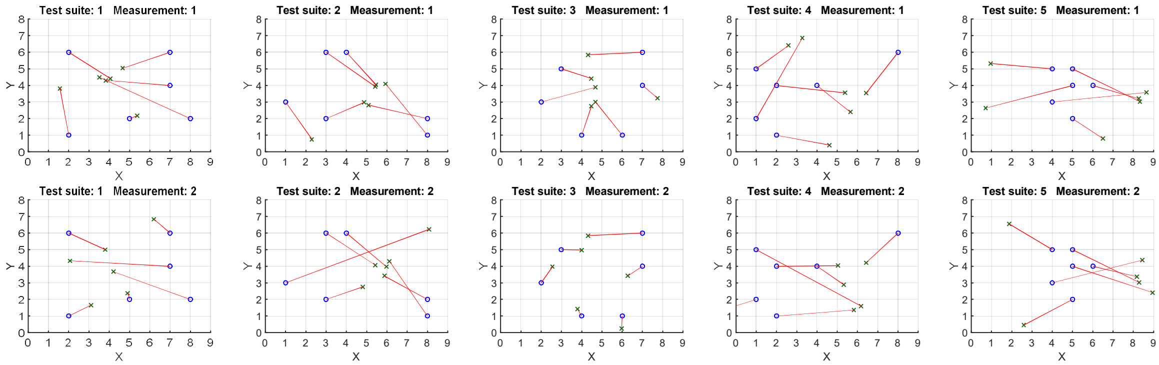

Fig. 3. Estimated and true smartphone positions

For the three scenarios, there were several positions (configurations) where the obstacles (people) were set (Table III). Fig. 4 represents scenario 2 (upper) and scenario 3 (lower) for distance of 4 meters between the measuring devices (blue person with the Device 1 at the left side and red person with the Device 2 at the right side in Fig. 4).

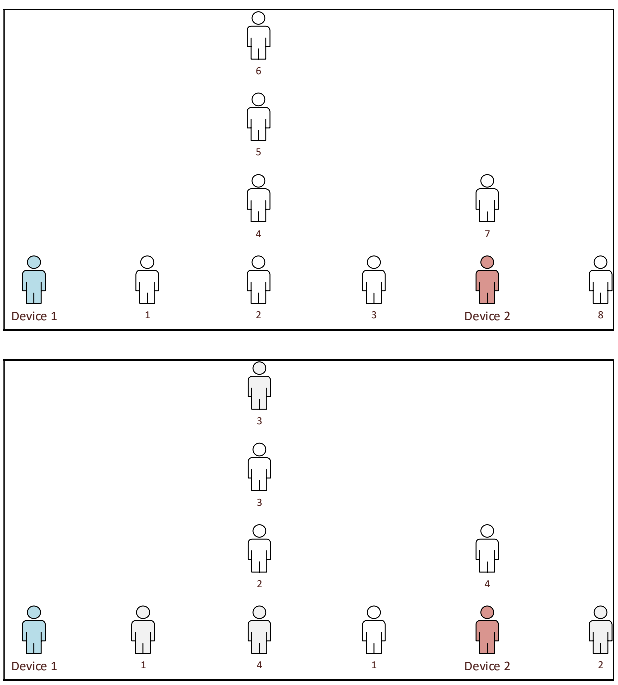

Fig. 4. The 8 configurations at the distance of 4m for scenario 2 (upper) and the 4 configurations at the distance of 4m for scenario 3 (lower)

In the second scenario (Fig. 4 upper), the person is positioned in the middle between the measuring devices (white person labeled with number 2), closer to one or another person (labeled with 1 or 3), at more distant position (labeled with 4, 5 and 6) or near the second measuring device (labeled with 7 or 8). In the third scenario (Fig. 4 lower), the obstacles are set between the measuring devices (white person and grey person labeled with number 1), at more distant position (labeled with 3) or near the second measuring device (labeled with 2 or 4). Signals were measured for 4, 6, 8 and 8 configurations at distance of 1, 2, 4 and 8 meters respectively for one obstacle/person around. For two obstacles/persons around, signals were measured for 2, 3, 4 and 4 configurations at distance of 1, 2, 4 and 8 meters respectively (Table III).

TABLE III. PARAMETERS AND SCENARIOS OF THE EXPERIMENT

Parameter	Setup
Distance	1m, 2m, 4m and 8m
Scenario (number of obstacles/persons around)	Scenario 1, without obstacles Scenario 2, one obstacle Scenario 3, two obstacles
Mode	Obstacle, Access point (WiFi), Talk
Number of different configurations	1/1/1/1 for 1/2/4/8m in Scenario 1 4/6/8/8 for 1/2/4/8m in Scenario 2 2/3/4/4 for 1/2/4/8m in Scenario 3
Measurement repetitions	2 x 2 ($RSSI_{1\to2}$ and $RSSI_{2\to1}$ with two repetitions)
Total measurements: 316 x 4 = 1264	

It is very important to stress out that the experiment was done through the repetition of measurements and that people performing the experiment were still and patient, turned to each other, trying to avoid any error in measurements caused by mishandling or the delay of the devices. In other words, although the experiment was done with real phones and people, it is still not representative as real-life situations where people are moving around holding their phones in different ways, and passing near variety of obstacles.

B. Results

In order to obtain the initial values and the reliability of the signals from our devices, we conducted extensive measurements of RSSI signals at distances of 1, 2, 4 and 8 meters, i.e. 40 measurements for each distance.

Table IV presents the average values, the standard deviation, and relative error. We achieved error from ±3.4dBm to ±5.9dBm, which is satisfactory since commonly tolerance stated in literature is from ±4dBm to ±8dBm.

TABLE IV. AVERAGE RSSI VALUES, STANDARD DEVIATION AND RELATIVE ERROR OF MEASUREMENTS

Distance	1m	2m	4m	8m
Average RSSI (dBm)	-41.1	-49.9	-57.4	-62.7
Standard deviation (dBm)	3.4	4.2	3.8	5.9
Relative error (%)	8.3	8.5	6.6	9.5

Fig. 5 shows spread of measurements for different modes at the distance of 4 meters.

The first whisker bar represents the spread of the measurements for the ideal situation where there is no obstacle between the devices, no person (except those with the measuring devices) and no WiFi devices nearby. The results are stable as expected, varying from -55dBm to -52dBm with the mean of 53dBm.

The second bar is the spread of the measurements when one person is near Device 1 or near Device 2, as in Fig. 4 (upper) for configurations 4, 7 and 8. The results are little bit more spread than in the first bar, ranging from -55dBm to -50dBm, with the mean of -53.25dBm, which is similar to the first bar.

The third and the fourth bar are the spread of the measurements when there is one person (with her device) near Device 1 or near Device 2 (see Fig. 4 upper, configurations 4, 6 and 7), acting as an Access point and talking respectively. The measurements are more spread than in the first situation, which was not expected (ranging from -73dBm to -49dBm and from -61dBm to -55dBm respectively, with the mean of -55.58dBm and -57.83dBm).

The fifth bar represents the result of the measurements when one person is acting as an obstacle (Fig 4 upper, configurations 1, 2 and 3). The results are more spread than in the first situation (ranging from -65dBm to -58dBm), as expected. The mean of the data shifted to -60.58dBm, which is 7.5 lower compared to the first bar.

The sixth and the seventh bar are the spread of the data measured when one person is acting as an obstacle and access point in the same time, or as an obstacle and talking on the phone at the same time, respectively. Very similar results as for the fifth bar (when one person is acting as an obstacle only - without a device) are expected. The mean of the data is much lower and the data is more spread (with the range from -74dBm to -57dBm and from -71dBm to -56dBm respectively and the mean of -65.75dBm and -66.25dBm respectively).

Finally, the last bar is the spread of the data when two persons are acting as obstacles between the measuring devices (Fig. 4 lower). This bar has the most spread and the lowest average value, which is expected. Still, the spread of the last bar is very big, meaning there is a very low reliability of the data.

We can conclude that adding noise or obstacles between the measuring devices will increase the spread of the data (decreasing the reliability) and will shift the mean of the data (yielding false distance values when converting the RSSI into distance).

Although most of the results are expected (like shifting the mean when noise or more obstacles were added), that information is not very useful for enhancement of RSSI-to-distance formula. First, in the real-life situations, it is hard to recognize the context in which the measurements will take place (is there one or more obstacles, other devices, etc.). Even a person holding her smartphone will act as an obstacle between the measuring device and her phone. Secondly, it is a time-consuming job to repeat the measurements in order to shift the average value closer to the realistic one, so the one should deal with the data she can collect (which can vary a lot, as we showed with this experiment).

IV. LESSONS LEARNT FROM RSSI ANALYSIS

The techniques for indoor localization which rely on distances obtained only from RSSI measurements do not provide satisfying performance by means of localization accuracy. Using very traditional (interpolation based) method for converting RSSI into distance, poor results were achieved. From our experimental settings, the following four main issues can be highlighted:

- Radio propagation model is dependent on environmental conditions (temperature, humidity, etc.) and is highly variant in dynamic environment. Therefore, choosing the appropriate model is not a trivial task.
- Initial smartphone calibration is different for different smartphone models, and it is not easy to embed this information into the conversion method.
- Irregular network topology (by means of presence of obstacle) decreases the RSSI compared to regular network topology.
- Network (device) density has effect on the relationship between the RSSI and the distance, since the presence of many communication devices (WiFi, modems, Bluetooth) in the monitored environment increases the interference.

The localization algorithms can be improved by adding additional sensors, like MEMS sensors [13], accelerometers [14], compass [15], acoustic beacons and smartphone microphone [16][17], or by combining with other technologies such as Bluetooth [18]. Some interesting variations and improvements in this area include exploiting the physical layer [18]. Algorithms can also be improved by repeating the measurements over time [15][20][21] or clustering of AP directions [22]. There is also trend of using alternative technologies, such as visible light band (especially LED light) for communication and positioning [23].

Therefore, we strongly encourage researchers to develop hybrid approaches that include other, more accurate ranging technique for distance estimation. Still, one should be aware of limitations of hybrid approaches in dynamic, continuously-changing crowded environments. The drawback is high computational complexity, resulting with high running time, even up to 60 seconds for some clustering methods [22], which is not feasible for real-time applications.

On the other side, solutions for indoor positioning should be robust enough not only to compensate for differences between smartphone models, but also to minimize the effect of different communication and non-communication devices on the positioning accuracy.

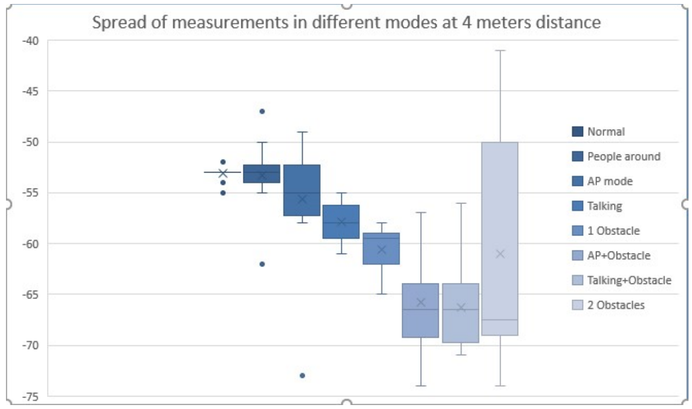

Fig. 5. The comparison of the RSSI measurements for different scenarios/modes at 4 meters distance

V. CONCLUSION

In this paper, we experimentally evaluated a well-known technique from the literature for localization of smartphones in indoor environments. Our results perform very poor localization accuracy under field condition, identifying signal strength conversion into distance to be the most challenging task of the localization pipeline. Still, introducing context information about the environment can lead to more accurate conversion of the signal strength into distances. Therefore, techniques based on RSSI can be used as a solid base for coarse grained localization, which can be improved by including other ranging techniques for distance estimation to obtain fine grained localization.

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