Comparison of measurement-based and simulation-based indoor Wi-Fi positioning algorithms

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***Abstract*—With the spreading of Wi-Fi networks, new services are provided. In particular, Wi-Fi networks can be used to locate mobile terminals based on measurements. In this paper, we propose a hybrid positioning model based on signal strength measurements and a probabilistic positioning system based on pre-computed signal strength map. Both models are tested in various environments and data sets and compared to well-known approaches.**

I. Introduction

In the past few years, wireless communications have been spreading over the world and are now available almost everywhere at very low costs. Wireless communications enabled the use of mobile devices with network connection. As users are now moving with their devices, new services can be provided, especially context-aware services. Such new services raise new issues such as service continuity and positioning.

Positioning consists in determining a mobile device geographical location. It is based on computation of various signals that can be acquired by the device or its infrastructure. A famous and typical example is the Glocal Positioning System [1], an outdoor system able to locate devices based on radio signals transmitted by satellites. However, indoor positioning cannot be achieved by regular satellite systems and is still under developpment. The main systems are based on Wi-Fi due to its throughput and presence everywhere. Indeed, it is possible to combine positioning and communication functions without requiring dedicated hardware to provide a positioning service.

This article deals with indoor positioning based on Wi-Fi signals. We present two models to locate a mobile terminal based on Wi-Fi signal strengths. The main goal of this paper is to compare performances of both models within two different testbeds: one is obtained through measurements whereas the other one is computed by signal propagation simulation. Both models are also compared to a selection of related works models.

The remainder of this paper is structured as follows: second section depicts current related work in the field of indoor positioning. Third section contains our contributions in terms of positioning models and algorithms. Fourth section describes tests we run and their results. Results are analysed to compare between simulated and measured signals and their impact on positioning accuracy. Finally, we draw conclusions from the analysis and we present our working perspectives.

II. Related Work

Whereas outdoor positioning is addressed by Global Navigation Satellite Systems, indoor positioning still remains unsolved. Some systems were proposed, based on various physical transmission media among whose Wi-Fi.

In Wi-Fi positioning systems, we can separate current work into two families.

One is based on signal strength map [2]. The map can either be constituted with measurements or with simulation[3]. Then, positioning is achieved by mathing real-time measurements to the signal strength map database content. The matching is either deterministic [4], [5] or probabilistic [6], [7], [8].

The other family is based on wave propagation modeling [9]. It works by computing the distances between a terminal and some access points whose coordinates are known. Some model are static [9] whereas others are calibrated [10], [11]. The distances allow to compute the terminal location by multilateration [12], [1].

Both families have their strengths and drawbacks. We present two models, both trying to address the drawbacks of state of the art systems.

III. Contributions

Given the analysis of related work, we propose in this section, two positioning models trying to tackle both positioning systems families drawbacks while keeping their best properties: quick setup and high accuracy. First model is based on an hybrid radio map and propagation-based system. Second one is based on radio map generated by simulation.

A. Hybrid model

FBCM and Reference-Based Hybrid Model (FRBHM) is based on FBCM [10] and radio map fingerprinting [2]. While a global propagation model is unaccurate, a sparse radio map allows the use of a local propagation model. Such model is based on a Friis formula with calibration (FBCM). This model tries to reach an efficient tradeoff between both positioning models families. While being technically different from differential GPS, its main idea is akin to it: finding an accurate local propagation model according to a first and coarse location calculation.

Two steps are required to deploy and use a hybrid model. First one is the offline step, during which a signal strength map is built: we store reference points in a database, defined by their coordinates, orientation and set of signal strength measurements linked to the source AP.

Second step is the positioning process performed in real-time and involving multilateration. It consists in locating a mobile device which sent a signal strength set measured from its current location. Based on these measurements, a research is performed in the reference points database. The closest point in signal strength space is selected.
The point selected from SS map is used to calibrate Friis relation according to its SS vector. It aims at increasing distance impact on signal strength. Basically, square power applied to distance is changed to a greater value, called Friis index, according to targeted indoor environment. Formula used to compute the Friis index, one per access point, is the following:

$$i = \frac{P_T - P_R + G_R + G_T + 20\log(\frac{\lambda}{4\pi})}{10\log(d)}$$

where P_T and P_R are powers transmitted and received, G_R and G_T are receiver and transmitter antenna gains, λ is the radio signal wavelength and d is the distance between the access point and the mobile device.
Based on these indices, distances between access points and mobile device are computed with the request SS vector. As access points coordinates are known, multilateration allows to compute a location for the mobile device.

B. Probabilistic positioning model over a simulated radio map

CMTA-WLAN-Based Positioning System (CMTA-WPS) is a probabilistic location determination system to estimate the user location as described in [13], which combines the Centre of Mass technique (CM) and the Time Averaging technique (TA) to the above system to further enhance its accuracy. CMTA-WPS uses a discrete-space estimation process that returns the radio map location that has the maximum probability given the RSS vector from different AP. CMTA-WPS works with a signal strength map generated by simulation. Generating the SS map allows to reduce setup time, thus tackling the SS map based systems drawback: a small sample of measurements are required to calibrate the simulator which, in its turn, will generate the signal strength map database.

As many usual positioning systems based on fingerprinting, CMTA-WPS works in two phases: offline phase and online, or working, phase. Since CMTA-WPS works on a discrete space, the radio map is decomposed by 1m $\times$ 1m grid and RSS from different Access Points on each grid node (MP) is calculated. To simulate the RSS probability distribution in the real environment, a model-based training scheme is proposed in two steps:

- smoothing probability distribution shape,
- adding heavy tail characteristics.

In the online stage, the mobile device detects a signal from each access point in an unknown location. The position-determination problem is to find a position, li, at which the probability $P(l_i/O)$ is maximized. Mathematically, this probability can be represented as:

$$P(l_i/O) = \frac{P(O/l_i)P(l_i)}{P(O)}$$

Where $P(O/l_i)$ is the conditional probability of obtaining observation O at position l_i , $P(O)$ is a normalizing constant; and $P(l_i)$ is the prior probability of position l_i being the correct position.

CMTA-WPS serves in context-aware applications such as guide systems and tracking systems, in which the movement of a mobile device is subject to the area topology. Therefore, a filter taking topology into account can be applied. It is based on previous locations and a weighted graph to represent the position topology. Then, a finite state machine is introduced to distinguish states of locations.

If more than one location has maximum probability, the Centre of Mass technique estimates the user location based on the list of candidate locations in the current estimation period. This technique is based on treating each location in the radio map as an object in the physical space whose weight is equal to the normalized probability assigned by a discrete-space estimation process. Time Averaging works in tracking mode. This technique estimates the user location using the history of consecutive estimates. It uses a time-average window to smooth the resulting location estimate.

IV. Experiments

We cross-tested both systems with two testbeds: the original one from FRBHM and the original one from CMTA-WPS. In this section, first we describe both testbeds and second, we analyse the results we got from our experiments.

A. Systems tested

We tested both systems we presented in section III, i.e. FRBHM and CMTA-WPS, as well as FBCM, RADAR (also referred to as “closest in SS space selection”) and Interlink Networks (also referred to as “fixed Friis index”) systems for comparison with our own models in exactly the same environment. We chose to implement and test RADAR and IN because they are both extremes in positioning systems family: RADAR is a pure radio map-based system whereas IN is a pure wave propagation-based system.

B. Testbeds descriptions

Both testbeds are described in this section. First, we describe Numerica testbed, second, we describe UTBM one.

1) Numerica: Experiments took place in first and second floors of the computer science laboratory of the University of Franche-Comté. Figure 1 shows both floors and illustrates the testbed. The experiments is based on real measurements. Access points are triangles heading up. Crosses are reference points stored in the SS map. There are 276 reference points available for testing. Another measurements set is used as test data and contains 86 points.

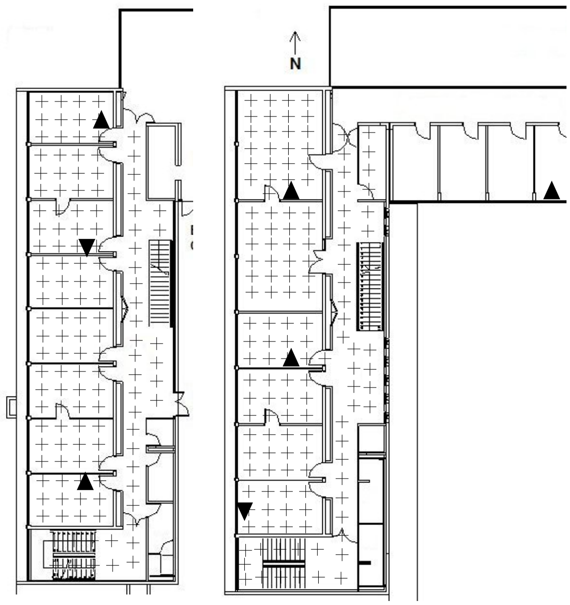

Fig. 1. Numerica testbed.

We denote that there are two main part on each floor: a corridor running all along one building side and offices separated by light walls along the other side. Both parts are separated by thick load-bearing walls which have a great impact on wave propagation. Each floor size is 11m × 33m.

2) UTBM: While the Numerica testbed is based on real measurements, the UTBM testbed is based on a radio map computed by a wave propagation model. The scenario for performance evaluation takes place at the second floor of a UTBM building. The experimental area is approximately 80m × 40m. We use 802.11g wireless LAN infrastructure to provide coverage. Test environment topology is described in figure 2.

From the figure, we can see that the topology is very irregular and complex in terms of wave propagation, thus being very difficult for location purpose. And from our previous research, we conclude that the well coverage of the test area and the symmetrical AP placement benefit to the accuracy of location. So in the real test scenarios we manually deploy the AP with a good coverage and with quite symmetrical configuration. For the analysis need, we selected 22 uniform distributed Reference Points (RP) where a series of measurements have been performed. RPs and APs are distributed on the whole floor as shown in the figure. Experiments are performed in two sets. First one concerns west part of the building, second

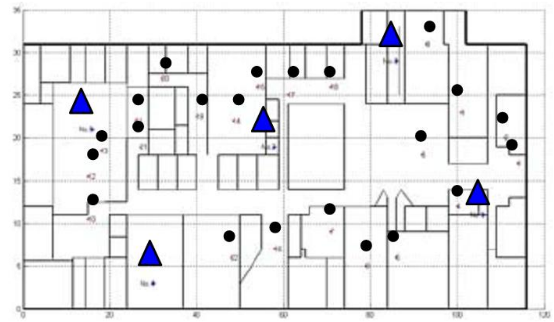

Fig. 2. UTBM test building and hardware and test points layout.

one concerns east part of the building. West part has 3 APs available whereas east part has 4 APs available.

C. Results

To test positioning algorithms, we use a test data set. It contains signal strength measurements as well as test point real coordinates. Algorithms performances are defined by their positioning error, i.e. the euclidean geographical distance between location computed by the system and real location.

We compare 5 algorithms, numbered as follows:

- (1) stands for RADAR system [2] (closest in SS space selection),
- (2) stands for Interlink Networks system [9] (fixed Friis index to 3.5),
- (3) stands for FBCM [10],
- (4) stands for FRBHM,
- (5) stands for CMTA-WPS.

3AP	(1)	(2)	(3)	(4)	(5)
1m	5.08	12.76	7.49	6.68	n/a
2m	5.19	12.76	7.30	7.00	n/a
3m	5.53	12.76	7.53	7.13	n/a
4m	5.51	12.76	7.59	6.92	n/a
4AP	(1)	(2)	(3)	(4)	(5)
1m	4.32	11.57	6.80	5.39	n/a
2m	4.22	11.57	6.47	5.53	n/a
3m	4.69	11.57	6.44	5.66	n/a
4m	4.82	11.57	6.66	5.59	n/a
5AP	(1)	(2)	(3)	(4)	(5)
1m	3.83	10.78	6.74	5.06	4.99
2m	3.65	10.78	6.30	5.13	5.44
3m	4.11	10.78	6.16	5.13	8.68
4m	4.49	10.78	6.34	5.24	6.14

TABLE I
AVERAGE ERROR (METERS) WITH NON-ORIENTED MOBILE DEVICE, NUMERICA TESTBED.

Table I shows results in Numerica testbed. We observe that when reducing RP grid density, accuracy decreases. When the number of available access points decreases, so does accuracy. Indeed, reducing the number of access points reduces the opportunity to disambigue some locations, e.g. it's easier to observe two similar locations in signal strength space with 3 access points than with 5 APs. It goes the same way with RP grid density: decreasing density leaves more space between RP, therefore less close candidates from a request SS vector.

We observe that closest in SS space selection is less impacted by RP density decrease than FBCM and FRBHM. Fixed Friis index doesn't vary with RP density due to its total independance from *a priori* data. However, it is very unaccurate.

Results in UTBM testbed are shown in table II. Results are unaccurate compared to Numerica testbed results. However, this is explained by a low number of access points (3 or 4) compared to testbed size (approx. 3200 m^2), while Numerica has 3 to 5 APs available for an approximate size of 350 m^2. Another source of unaccuracy is the SS map computation using a propagation model. Indeed, the propagation model used is not accurate enough to take into account a complex environment such as the UTBM testbed.

We also observe an erratic accuracy when varying RP grid density for UTBM testbed. Indeed, varying density is achieved by filtering x-coordinates and y-coordinates from RP data and it can lead to configurations where most of reference points are close to walls, with higher variation and other configurations with more "stable" reference points.

Finally, we observe that the test for 4 APs returns very bad results. It is bound to a topology more heterogeneous than the 3 APs one.

4AP	(1)	(2)	(3)	(4)	(5)
1m	8.9	19.79	99.25	12.74	8.31
2m	9.12	19.79	19.38	13.39	n/a
3m	11.26	19.79	17.5	13.68	n/a
4m	10.23	19.79	18.35	14.19	n/a
3AP	(1)	(2)	(3)	(4)	(5)
1m	6.01	8.87	33.55	6.52	4.65
2m	5.17	8.87	9.07	6.78	n/a
3m	6.26	8.87	11.65	7.09	n/a
4m	4.94	8.87	7.22	6.6	n/a

TABLE II
AVERAGE ERROR (METERS) WITH NON-ORIENTED MOBILE DEVICE, UTBM TESTBED.

When comparing between systems, we see that closest in SS space selection always gets best accuracy, followed by FRBHM, FBCM and fixed Friis index. Surprisingly, even when reducing RP grid density, simple SS map approach remains the best choice.

Another interesting result is the comparison between measured SS map and computed SS map. To compare both ways of getting a SS map, analysis is made on 3 APs, as their results are stable in UTBM testbed. We see that results seem close. It means that a proper propagation model can meet positioning systems requirements in terms of accuracy. It is also a proof that measurements can build a SS map, even considering SS variation over time.

However, computed SS map cannot allow to use FBCM. It seems that SS values bias between measurements and simulation are too large to resort on a pure propagation-based system when using simulated training data.

V. CONCLUSIONS AND FUTURE TRENDS

A. Conclusions

In this paper, we presented various positioning algorithms, either based on propagation models or signal strength maps, with matching being deterministic or probabilistic. Models were tested in two environments, one built over measurements whereas the other one is built through simulation by an average accurate propagation model, although there exists better propagation models for radio networks planning. However, even the most accurate propagation model would not take into account variation due to dynamic factors such as doors and furnitures that can be moved and people moving in the environment.

Both FRBHM and CMTA-WPS show good performances to provide positioning support to context-aware applications. They confirm that either simulation or measurements can address SS map creation in a positioning system. They also prove that pure propagation-based systems are not accurate enough to provide positioning. On the opposite, all tests prove that SS map-based systems and hybrid systems meet accuracy requirements for context-aware applications.

B. Future trends

However, some points require to be clarified. First, comparison should be performed in same conditions for computed SS map and measured SS map. This is the proof required to definitely compare both methods.

Moreover, further testing on the computed SS map are planned in order to study if the erratic behaviour we observed will occur again or if it is a matter of topology and arbitrary reference points selection.

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