The EVARILOS Benchmarking Handbook: Evaluation of RF-based Indoor Localization Solutions

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***Abstract*—RF-based indoor localization solutions enjoy consistent efforts of researchers to provide more accurate and sustainable solutions. The multiplicity of RF-based indoor localization solutions makes their evaluation an indispensable part of future Internet. However no unified scheme has been devised for evaluation of these solutions and their robustness against various parameters. To remedy this, the EVARILOS handbook is created in order to objectively evaluate and compare different indoor localization solutions. In this work, we present an overview of the EVARILOS project whose objectives are the development and validation of standardized experiment-based benchmarks for localization solutions.**

I. Introduction

Accurate and robust indoor localization is a key enabler for context-aware Future Internet applications, whereby robust means that the localization solution should perform well in diverse physical indoor environments under realistic RF interference conditions. However, despite the abundance of works on RF-based indoor localization solutions, the numerous published solutions are evaluated under individual, not comparable, not repeatable and often not realistic conditions. No unified scheme is provided for the fair comparison and evaluation of various solutions. Therefore it is necessary to develop and establish a comprehensive benchmarking methodology which is able to consider variety of existing solutions and their significant features. The EVARILOS project (**Eva**luation of **R**F-based **I**ndoor **Lo**calization **S**olutions for the Future Internet) [1] focuses on the development of the benchmarking methodology which consists of providing (i) metrics for evaluation of RF-based indoor localization solutions and (ii) a set of benchmarks and scenarios which are recommended to use for experimental performance evaluation according to the previous metrics for a given solution.

The main outcomes of the project are a public handbook on the use of the EVARILOS benchmarking methodology and the EVARILOS benchmarking suite. The benchmarking suite will be publicly available under open source licenses and implemented in two different testbeds belonging to the FIRE facilities (FP7 CREW [2] and FP7 OpenLab [3]), more specifically on the testbeds in Berlin and Ghent. The EVARILOS project uses the OMF [4] control and management framework and mobility support features developed in OpenLab and will further use and extend the benchmarking features from CREW. An open challenge is also envisaged using the above mentioned testbeds to invite external experimenters for evaluation of their localization solutions and use their feedback and results together with the results of our own experiments to create the first repository of localization solutions evaluated using a unified methodology.

The rest of this paper is organized as follows. The next section handles about the state-of-the-art of indoor localization. The benchmarking methodology in Section III describes the general structure of the benchmarking handbook. The scenarios, environment and metrics are further explained in respectively Sections IV, V and VI. In Section VII, the future work of the EVARILOS project is described. Finally, conclusions are made in Section VIII.

II. Related work

Generally, there are two phases towards realization of accurate location-based applications: **ranging** and **location estimation**. A state-of-the-art overview is given of existing ranging techniques and location estimation methods.

A. Ranging

Localization methods can be divided into two categories [5] *range-based* and *range-free*. The former is defined by protocols that use absolute point-to-point distance estimates (range) or angle estimates for calculating location. The latter makes no assumption about the availability or validity of such distance or angle information. Range-free methods are found in rather theoretical, not empirical work. [6] compares two range-free localization algorithms. In environments with obstacles, many range-free techniques that have been proposed to improve the localization accuracy are useless and inversely decrease the algorithm's accuracy [7]. The most commonly used techniques to perform ranging are:

RSSI (Received Signal Strength Indication) is an indication of the power level received by a receiver expressed in dBm. This value is then used to estimate the distance between transmitter and receiver. The physics behind this technology is the power level decay with distance. RSSI is available in most RF receivers.

ToA (Time of Arrival), also called ToF (Time of Flight), uses the travel time of a radio frequency wave from one transmitter to one receiver. With the speed of light the distance is calculated. ToA requires precise synchronization of timers at both transmitter and receiver.

TDoA (Time Difference of Arrival) is also based on the speed of light. Here the position is calculated with at least three spatially separated receiver sites (and one transmitter, being the object to be localized). The difference of the time of arrival at two receivers will narrow the possible position to one half of a twosheeted hyperboloid. The knowledge of the time of arrival at the third receiver is needed to calculate the unknown position. TDoA only requires precise synchronization at the receivers. In many wireless sensor networks, TDoA is based on the time difference between simultaneously transmitted radio and ultrasound pulses as in the Cricket system, as typical WSN clocks are too slow for the first approach only [8].

AoA (Angle of Arrival) determines the angle of an incident RF wave, which requires special antennas such as antenna arrays. AoA methods based on antenna arrays determine the direction by measuring the time difference of arrival (delays) at individual antenna elements of the array. From the delay measurements at the individual antenna elements, the angle of arrival can be calculated. Because most antennas are reciprocal, this can be considered as reverse beamforming.

DTDoA (Differential Time Differences of Arrival) uses the difference of TDoA measurements. This is done to overcome the time synchronization of both transmitter and receivers. This is accomplished by introducing a fourth anchor that is responsible for initiating the TDoA measurement by transmitting a special message. In this way the anchors' time offsets can be computed [9].

Proximity uses a very weak sending power, if a message is received, the receiver knows it is the vicinity of the sender. We cannot infer anything, if the message is not received.

Hybrid techniques are the combination of any of the previous techniques.

An overview of the different ranging techniques with the different wireless technologies can be found in Table I.

B. Location estimation

Once the ranging measurements are available between the fixed anchor points (whose position is already known) and the (mobile) object to be located (whose position is unknown), it is possible to utilize several methods for the estimation of the location of the object.

A first distinction can be made between fingerprinting or not, typical for a fingerprinting is the use of a large database and training phase. This database is filled with measurements (e.g. the RSSI-values recorded by nodes knowing their own position) during the time consuming (in the order of several days) off-line phase (also called training phase). The online phase is the positioning of a target: here a new measurement is compared to the values in the database. The stored measurement that is closest to the measurement of the target gives the estimated position. A drawback of this method is that the database needs to be filled with new measurements if the environment changes (e.g. adding a new bed in a hospital localization system [10], [11]). Non-fingerprinting methods do not require an off-line phase and these methods are faster.

A distinction is based on the usage of geometric techniques or statistical methods. Geometric techniques use geometry to calculate the position from at least three ranging measurements. An example is geometric multilateration [12]. The use of statistics is widely accepted in location estimation. Here, the frequency distribution of the distances is considered for making an estimation of the position. Mainly, there are three different methods: statistical multilateration, maximum likelihood estimators and Bayesian estimators.

In its simplest form statistical multilateration [12] minimizes the sum of the squares of the ranging errors (e.g. distance errors). There also exists a weighted least square approach, like in [13]. Here the measured values are first weighted, before the minimization: e.g. high RSSI-values are given a higher weight. In indoor environments this leads to the unjust preference of the paths with the most constructive multipath fading according to a study recently performed by iMinds [14].

Maximum likelihood methods make use of a cost function. Dependent on the kind of cost function, it needs to be minimized or maximized to find the most likely position. Several cost functions exist. In [15] the simplest and most widely accepted method (minimum mean square error) is presented. Some more cost functions, not only for RSSI but also for ToA measurements, are presented in [16]. A linear regression based cost function is introduced by iMinds in [17].

Bayesian localization methods are based on Bayes' theorem [18] and therefore incorporate some prior knowledge in the estimator. Two extensively used methods are Kalman filters, Particle filters [19], [20] and hidden Markov models (HMM) [21]. Another example of a Bayesian method can be found in [22].

III. BENCHMARKING METHODOLOGY

As stated earlier, the EVARILOS project addresses one of the major problems of indoor localization: the pitfall to reproduce research results in real life scenarios and the inability to compare their performance due to evaluation under individual, not comparable and not repeatable conditions. The EVARILOS handbook presents a benchmarking methodology that remedies these shortcomings, by defining objective experimental validation of and fair comparison between state-of-the-art indoor localization solutions under different use-case scenarios and configuration setups.

Contrary to previous approaches, the EVARILOS benchmarking methodology does not focus exclusively on the accuracy of the evaluated localization approach, but also considers other important criteria that are relevant in view of the commercial deployment of localization solutions such as complexity, interference robustness, cost, energy efficiency, etc. Since different use cases have different sensitivities for individual metrics, the EVARILOS benchmarking methodology cleanly decouples between the metrics and the calculation of the final score used for ranking. As illustrated on Figure 1, after collecting a set of measurements necessary for the calculation

TABLE I. WIRELESS TECHNOLOGIES FOR INDOOR LOCALIZATION VERSUS RANGING TECHNIQUES

	Ultrasonic	Infrared	IEEE 802.15.1	RFID	IEEE 802.11	IEEE 802.15.4a DSSS	IEEE 802.15.4a UWB	IEEE 802.15.4a CSS	60 GHz
RSSI	✗	✗	✓	✓	✓	✓	✓	✗	✗
ToA (ToF)	✓	✗	✗	✓	✓	✓	✓	✓	✗
TDoA	✓	✗	✗	✓	✓	✗	✓	✗	✗
DTDoA	✗	✗	✓	✗	✓	✗	✗	✗	✓
AoA	✓	✗	✗	✓	✓	✓	✓	✗	✗
Proximity	Obstacle avoidance	✓	✓	✓	✓	✓	✗	✗	✗

Fig. 1. Transform measurements to scores using metrics

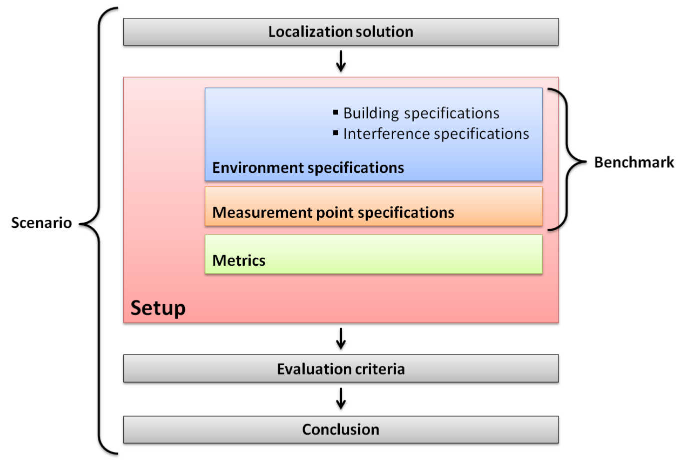

Fig. 2. Structure of a scenario

of the individual metrics, the EVARILOS methodology allows application of specific weighting factors for the calculation of the final ranking score that reflect the different impact of the metrics for the different application scenarios of interest.

In the EVARILOS point of view, a benchmark is an evaluation method that is used to evaluate and compare the performance of one or more localization solutions. A benchmark is a combination of environment specifications, the setup and unambiguously defined performance metrics. An EVARILOS benchmark allows a fair and objective comparison of different localization solutions such that they can be ordered by a binary relation $\leq$. The object of comparison is the benchmark score(s).

IV. SCENARIOS

A scenario fully describes a benchmark, and consists of a definition of the used metrics, the criteria of the evaluation and all the necessary parameters and traces to perform the experiment. A scenario description is a combination of an *environment description*, a *setup description* and specification of the *metrics*. This is illustrated in Figure 2. All evaluations are considered black box benchmarks: the scenario description can be seen as a black box, which takes as input a localization approach, and outputs one or more numerical benchmarking values. As such, the internal properties of the localization scenario are not evaluated, only its relevance for different application domains [23].

The next two sections elaborate on the environment specifications and the evaluation metrics of a scenario.

V. ENVIRONMENT DESCRIPTION

An environment specification is the description of the physical environment and the infrastructure that is used to perform an experiment. An environment is typically represents a real-life situation, for example an office environment. As such, the environment description defines both structural properties of the environment (e.g. room layout, room sizes, types of walls, etc.) and RF interference properties (e.g. what types of external RF technologies are present and to what extent). The performance of a localization solution is always related to a specific environment. The environment consists of two parts: the building specifications and the interference specifications of the environment.

A. Building specifications

Building specifications represent the infrastructure of a specific environment. In the benchmarking handbook, three types of walls are determined: open space (no walls), (ply)wooden walls and brick walls. For each type of wall, a corresponding room size must be selected (Small, medium or big). Since the performance of a localization solution is often strongly related to the type of environment, all benchmarking outputs must always be given together with a description of the building specifications. For fair comparison, the handbook describes in detail a number of predetermined reference building types.

B. Interference specifications

The list of interference specifications is more complex than the building specifications. Four different types can be distinguished: no, low, moderate and high interference. There are many parameters that define a certain interference profile. (i) Network parameters, e.g. network size, node density, mobility or failures, etc. (ii) Traffic parameters, e.g. packet size, inter packet gap, bitrate, filesize, start & stop time, traffic model, etc. (iii) Parameters of the interference source, e.g. number of sources, power, waveform, pattern, etc. and finally (iv) different types of interference, e.g. microwave, WiFi, Bluetooth, 3G, Zigbee, etc. Interference can be created artificially, or by replaying previously captured interference traces. Again, for fair comparison, the handbook describes a number of predetermined reference interferences types.

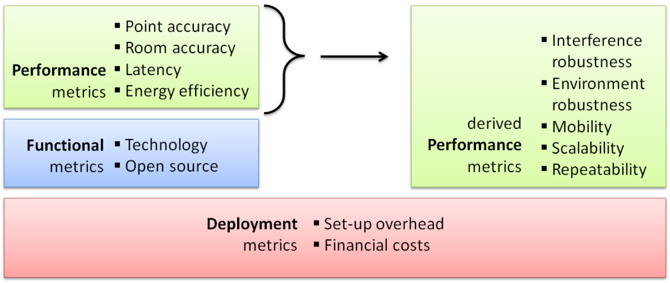

Fig. 3. Tree structure of the metrics

VI. Metrics

A metric is a measure of a specific performance indicator of the system under test. Depending on the type of metrics, for example accuracy, installation costs, etc., metrics are classified as deployment, functional or performance metrics. For comparing the suitability of a solution for a specific application domain, weight factors are assigned to the different metrics.

The EVARILOS benchmarking methodology takes into account the multifaceted nature of localization schemes and strives to define an adequate ensemble of metrics for evaluation process. For each individual metric, a definition is given, together with instructions for collecting the necessary underlying measurements and a mathematical formula that should be used for processing those measurements in order to calculate the metric value. The metrics that should be calculated depend on the application scenario, that describes which metrics are required, and which weighting factors are used for the calculation of the final ranking score. For each metric of interest, the handbook then recommends a set of benchmarks for the experimental assessment of the performance. The metrics are organized in three generic categories: performance metrics, deployment metrics and functional metrics. A structural overview is given in Figure 3.

The first and largest category is comprised by several metrics that try to capture different performance aspects of the system under test, such as its accuracy, robustness, scalability, etc. In this category, a distinction between the primary performance (Subsection VI-A and VI-B) and derived performance metrics (Subsection VI-C and VI-D) is made. The latter can be measured using the primary performance metrics. These, so called derived performance metrics, represent the sensitivity of the solution to different (external) factors, such as interference or mobility speed.

To calculate them, the accuracy is first measured in simple controlled environments before determining the sensitivity to external changing conditions. The functional metrics focus on non-performance related attributes like the underlying technology, licensing modalities, open-source availability, etc. Finally, the deployment metrics capture important properties related to the efforts and costs needed for physical installation, configuration, and replacement time.

A. Accuracy

In the EVARILOS benchmarking, two different accuracy metrics are usually used: point and room accuracy. With point accuracy, the actual Euclidean error distance between a reference point and a measured point is calculated. Suppose the reference point has coordinates (x_1, y_1, z_1) and the measured point (x_2, y_2, z_2), than the error distance d can be found by using Equation 1 for a 2D and Equation 2 for a 3D coordinate system.

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{1}$$

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{2}$$

Once the distances of the multiple tests are calculated the mean, standard deviation, minimum and maximum values can be calculated using the following equations:

$$\overline{d} = \frac{1}{n}\sum_{i=1}^{n} d_i \tag{3a}$$

$$\sigma_d = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i - \overline{d})^2} \tag{3b}$$

$$d_{min} = \min(d_1, d_2, ..., d_n) \tag{3c}$$

$$d_{max} = \max(d_1, d_2, ..., d_n) \tag{3d}$$

For some applications, room accuracy is required instead of point accuracy. When room accuracy is required, the localization solution only needs to identify the room in which the node is located. A distinction is also made between different floor levels.

To visualize the results of the room accuracy, a room confusion matrix is used. Each column of the matrix represents the instances in a predicted room, while each row represents the instances in an actual room. An example of a confusion matrix is given in Table II with the assumption that each room is located next to each other and each room is tested 10 times. In Table II the number of correct rooms is in bold (the predicted room corresponds to the actual room). The other numbers are the amount of incorrectly predicted rooms. With these numbers, a simple success rate can be calculated by dividing the number of correct rooms by the total number of rooms available. This becomes clear in Equation 4. Even more sophisticated success rate equations can be used where the geographical position of the rooms can be taken into account.

$$sr = \frac{\textit{number of correct rooms}}{\textit{total number of rooms}} \tag{4}$$

Both for point and room accuracy, a localization path is constructed that is representative of the application requirements, and which includes measurements points both near and far away from walls.

TABLE II. A confusion matrix: example

		Predicted room				
		Room 1	Room 2	Room 3	Room 4	Room 5
Actual room	Room 1	**7**	2	1	0	0
	Room 2	1	**8**	1	0	0
	Room 3	1	2	**6**	0	1
	Room 4	0	1	0	**9**	0
	Room 5	0	0	2	1	**7**

B. Latency and Energy Efficiency

Latency is a metric that represents the response time of the localization system, i.e. the time that system needs in order to update the location after the request for location estimation. Latency is measured by the time interval between the beginning and end of localization procedure of a node. Latency of the localization is an important metric because some localization use-cases such as emergency services require fast response time.

Energy efficiency is another metric which can be important particularly for wireless sensor networks (WSNs) where nodes must function completely wireless, and therefore are not connected to the power grid. The result of the measurement hardware is power and is expressed in Miliwatt (mW). The unit, defined as one joule per second, measures the rate of energy conversion or transfer ($W = \frac{J}{s}$). These measurements span a certain period but will only start once the system is up and running. For this metric, the same equations (average, min, max, ...) are derived as for the accuracy metric (Equations 3). Since the localization infrastructure is sometimes connected to power grid, a distinction is made between the power efficiency of the infrastructure and the clients.

C. Interference and Environmental Robustness

The RF-based indoor localization approaches are subject to exogenous interference caused by coexisting devices and technologies and endogenous interference caused by the other nodes using the same technology. The interference effect on the performance of localization schemes is measured by investigating the degradation of the accuracy under different interference circumstances. Different types and amounts of interference are specified and generated to study the interference robustness of this scheme, including competing wireless technologies but also microwaves and synthetic interference.

On the other hand, the RF indoor localization approaches are naturally exposed to the difficulties of indoor environment. Indoor environments are susceptible to changes caused by variation of network topology, room layout, walls, and channel conditions. The environment robustness determines if a solution is stable operating in different environments.

To measure these metrics, two different phases are necessary. The first phase is to calculate a metric from Section VI-B in well-defined and controlled environments (e.g. accuracy with interference or latency with mobility). The second phase is to compare the mean, standard deviation, minimum and maximum value of this derived metric with the original performance metric.

D. Mobility, Scalability, Repeatability and Reproducibility

One important feature of wireless networks is the variable topology of the network due to the mobility and varying number of users in a given area. The mobility metric is defined as the variation of performance metrics with the speed of the localized node and characterizes how the performance of the localization schemes is changing from low-mobility regime to high-mobility one.

The scalability metric is concerned with the density of nodes and characterizes the performance of the localization schemes in sparse and dense networks. To measure these metrics, two scenarios are defined and compared with for each case corresponding respectively to low/high mobility regimes and low/high density regimes.

Repeatability implies that, if the same benchmark runs twice, results in the same score under well determined conditions. However, this equality is not strict in wireless benchmarking due to a certain level of indeterminism. For repeatability to apply, acceptable error margins should be formally defined. To evaluate this metric, the solution will be reinstalled multiple times in the same testbed under the same conditions and the variation in the accuracy is checked.

Reproducibility is an extension on repeatability, where, if the same benchmark runs twice on a different testbed or location that represents the same environment, it should produce the same results. The same error margins on equality apply as in repeatability.

VII. Interference Robustness and Environmental Awareness

Environmental awareness and coexistence with other users and/or technologies is one of the core requirements of the Future Internet. This can be seen by the great push towards cognitive radio/dynamic spectrum access [2] in the wireless research community, but also by the attempts to add awareness and cognitive features to existing standards. As such, a secondary goal of the EVARILOS project is the development and evaluation of localization solutions that add RF interference robustness to (existing) indoor localization solutions, such that indoor localizations also perform well in real-life Future Internet environments which are subject to uncontrolled interference.

One approach to enhance the robustness of indoor localization is to utilize the information gathered for environmental awareness and coexistence for the assessment of the quality of the localization process. A wireless device operating in the Future Internet will typically have detailed information about its spectral environment, either through spectrum sensing, or information retrieved from a database. Based on this information it can e.g. choose the best (i.e. least interfered) frequency to be used for the localization procedure. Alternatively, it can at least adjust the expected precision of the result based on the amount of expected interference.

The goal of the evaluation of interference robustness in EVARILOS project is adding a new class of approaches to RF-based localization to combat interference drawbacks. The solutions will be evaluated using the above described benchmarking methodology. We investigate to which extent such cognitive functionality of environmental awareness can improve the robustness of indoor localization against interference. From the investigations we will derive guidelines for the different classes of localization approaches on how to use which information to increase the interference robustness of indoor localization.

VIII. Conclusion

This paper presents an overview of the EVARILOS project which targets benchmarking and evaluation of indoor localization solutions. The general benchmarking methodology is presented. This methodology is a collection of scenarios that consist of environment and interference descriptions and different evaluation metrics. As the primary benchmarking metrics we define point and room accuracy, latency and energy efficiency. The secondary metrics, derived from them, evaluate the localization schemes under different environments, interference profiles, mobility, scalability and repeatability. By assigning different weight factors to these metrics, the benefits of different localization solutions for specific application domains can be compared objectively. During the project, selected localization solutions will be used as representative samples from different classes of existing RF-based indoor localization solutions.

The EVARILOS benchmarking methodology is currently being implemented on two testbeds belonging to the FP7 FIRE facility project CREW: Berlin testbed and Ghent testbed using IEEE 802.11, IEEE 802.15.1, and IEEE 802.15.4 technologies. We will experimentally apply the benchmarks to selected solutions on the two testbeds, in order to prove that the EVARILOS benchmarking methodology is generally applicable in different testbeds.

Once the EVARILOS benchmarking handbook is in a final version, a benchmarking suite will be developed in order to make an open call for participation possible. With this suite, an open call experimenter can test his localization solution in the two testbeds described above. In this way, a fair comparison between the experimenters' solutions can be made using the EVARILOS benchmarking handbook. The handbook includes a detailed list of metrics that determine the quality of the solution, together with well defined scenarios so that the experimenter has the all the information needed to perform the experiment and evaluate his solution in the testbeds provided by the EVARILOS project. Simultaneously there will start several tests of localization solutions with and without interference. These measurements will be used to fine tune the benchmarking handbook.

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