Infrastructure for Benchmarking RF-based Indoor Localization under Controlled Interference

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***Abstract*—The proliferation of RF-based indoor localization solutions raises the need for testing systems that enable objective evaluation of their functional and non functional properties. We introduce a testbed and cloud infrastructure for supporting automatized benchmarking of RF-based indoor localization solutions under controlled interference. For evaluating the impact of RF interference on the performance of benchmarked solution, the infrastructure leverages various interference generation and monitoring devices. The infrastructure obtains location estimates from the System Under Test (SUT) using a well defined interface, and the estimates are subsequently processed in a dedicated metrics computation engine and stored in the dedicated engine for storing the results of benchmarking experiments. The infrastructure further includes a robotic mobility platform which serves as a reference localization system and can transport the localized device of the evaluated indoor localization solution in an autonomous and repeatable manner. We present the accuracy of our autonomous mobility platform in two different setups, showing that, due to the high accuracy, the location estimation provided by the platform can be considered as the reference localization system for benchmarking of RF-based indoor localization solutions. The results, as well as the raw data from the benchmarking experiments, can be stored into the dedicated publicly available services which gives the opportunity of reusing the same data for benchmarking different solutions. Finally, we present the capabilities of the testbed and cloud infrastructure on the use-case of benchmarking of an example WiFi fingerprinting-based indoor localization solution in four different interference scenarios.**

***Index Terms*—indoor localization, benchmarking, experimentation, evaluation, testbed infrastructure, cloud services, Radio Frequency, interference, generation, mobility, monitoring**

I. Introduction

Localization in urban environments and buildings, where people spend most of their time, draws lots of research attention nowadays. Due to the poor indoor performance of the Global Positioning System (GPS), a number of alternative localization approaches have been recently proposed. Among all those approaches, one of the most promising is Radio Frequency (RF)-based localization, using some characteristics of wireless signals to localize a mobile device. Particularly interesting is the 2.4 GHz Industrial, Scientific and Medical (ISM) band, due to its availability and various technologies already operating in these frequencies, e.g. IEEE 802.11, IEEE 802.15.4 and IEEE 802.15. This trend can be seen in the research community, while various localization approaches of such kind have been proposed, some examples being [1]–[3].

The performance of RF-based indoor localization solutions is usually being evaluated using local experimental setups in different environments, thus making different benchmarks hardly comparable due to differences in size and type of environments. The evaluated indoor localization solution is typically being carried by a test-person to each evaluation point, introducing inaccuracies due to errors in positioning and orientation of a person and influence of the person's body on the evaluated solution. The results are typically captured following different evaluation scenarios and using non-standardized metrics, with different number, density and locations of evaluation points. Furthermore, the influence of RF interference is usually being neglected or only marginally considered in the current benchmarks of RF-based indoor localization solutions, while it is shown that RF interference can indeed influence the performance of RF-based indoor localization [4].

Due to above specified reasons, current benchmarks are hardly repeatable and comparable, which reduces their objectiveness. While the steps towards the standardization of benchmarking methodology have been done in the EVARILOS Benchmarking Handbook (EBH) [5], which is aligned with the upcoming ISO/IEC 18305 standard "Test and evaluation of localization and tracking systems", the lack of tools for executing benchmarking experiments is still present. Some early considerations on this topic, which are significantly extended in this paper, are recognized in our previous work [6], [7]. Our aim on addressing this issue is twofold: 1) We present the testbed infrastructure for supporting objective benchmarking of RF-based indoor localization solutions without the need of a test-person and with the ability to generate artificial RF interference in the environment. 2) We present the publicly available cloud infrastructure for unified calculation of the performance metrics and for storage of raw data and experimental results of indoor localization benchmarking experiments. To our knowledge, the infrastructure for supporting objective benchmarking of RF-based indoor localization presented in this paper is the first publicly available infrastructure specifically designed for this purpose.

The rest of the paper is structured as follows. Chapter II gives an overview of the flow of indoor localization benchmarking experiments, while Chapter III overviews the RF hardware components available as the part of our testbed environment. Furthermore, Chapter IV presents the autonomous mobility platform and evaluates its accuracy in two different

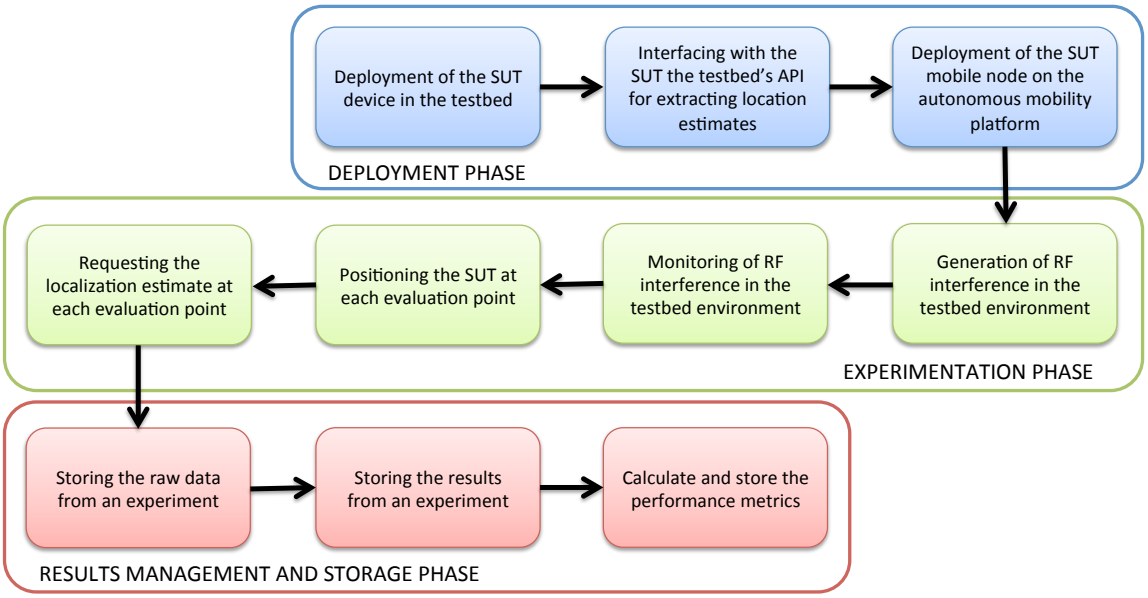


Fig. 1: Flow diagram of the benchmarking experimentation procedure

setups. Chapter V presents different functions of the testbed, namely, interference generation, monitoring and autonomous mobility, and instantiates different components for a specific purpose. Chapter VI describes the cloud components of the infrastructure, namely calculation and storage of evaluation metrics and storage of raw data of indoor localization benchmarking experiments. Finally, Chapter VII presents example experiments using WiFi-based fingerprinting algorithm as a SUT, while Chapter VIII concludes the paper and gives directions for the future work.

II. Overview of the Flow of Benchmarking

The overview of the envisioned flow of benchmarking experiments is given in Figure 1. In the first phase of benchmarking experiments, i.e. the deployment phase, the user has to deploy the infrastructural nodes of the SUT in the testbed, deploy the mobile node of the SUT on the mobility platform, with mobility platform being any means of transport of a mobile node in the later steps of benchmarking procedure, and accommodate the SUT in order to provide location estimates meaningful for the testbed's Application Programming Interface (API). During the experimentation phase the user is firstly able to generate different RF interference patterns and monitor the wireless spectrum. Secondly, the user can start the benchmarking experiment, meaning that it can position the mobile node of the SUT to different locations in the testbed's environment. Upon coming to each location the SUT is requested to provide an estimate, which is together with the ground truth location and the response time of the SUT sent for further processing. In the third phase of the experimentation the results have to be stored and metrics characterizing the performance of the evaluated SUT have to be calculated and finally also stored. Except for the benchmarking results, optionally the raw data of the experiment can also be stored.

For achieving the above described flow of benchmarking experiments we propose the infrastructure for supporting objective benchmarking of RF-based indoor localization in the environment with controlled interference. The proposed infrastructure has two main functional components: testbed infrastructure for performing benchmarking experiments and cloud services for calculation of the performance metrics ans storage of the raw data and results of benchmarking experiments.

Our remotely accessible and controllable testbed infrastructure is designed for supporting benchmarking of RF-based indoor localization solutions in the environments without and with artificially created RF interference. Our infrastructure leverages an autonomous mobility platform which enables accurate and repeatable positioning of indoor localization SUT and removes the necessity of manual rearrangement of a localized device. Furthermore, it integrates devices for generating controlled RF interference, that can be used for evaluating the influence of RF interference on the performance of the indoor localization SUTs. For validation of the resulting RF context, the infrastructure features monitoring devices that monitor the RF spectrum at different locations in the testbed in order to guarantee equal conditions for all evaluated SUTs.

Second, we propose a publicly available set of services for storing raw data and results of indoor localization benchmarking experiments and for calculating an extensive set of metrics that can characterize the performance of indoor localization solutions in an accurate and comparable way. The important metrics that characterize the performance of the indoor localization solutions are detected in our previous work [5], [8], and range from point and room level accuracy of location estimation to response time and power consumption of the SUT. The data from the service for storing raw data of indoor localization benchmarking experiments can be reused

on different indoor localization solutions using the same type of data, allowing to compare the performance of different SUTs on the same set of data, thus making the comparison between them entirely objective. Furthermore, the data stored in the service for storing the results of indoor localization benchmarking experiments can be used to compare the performance of newly evaluated indoor localization solutions with the already evaluated ones. Also, the service can be used as a portfolio of benchmarked solutions, where users can find the best indoor localization solution fulfilling their particular requirements.

Testbed and cloud infrastructure can be used jointly, creating a full chain for experimental benchmarking of RF-based indoor localization. Using the testbed infrastructure it is possible to generate artificial interference scenarios, monitor interference and use the autonomous mobility platform to navigate an evaluated indoor localization SUT in the environment and request the estimates from the SUT over a well defined API. Further, it is possible to sequentially feed ground truth locations, estimates, times needed by the SUT to produce the estimates and raw data used to produce them into the cloud infrastructure.

However, cloud services can also be used without the testbed infrastructure. Firstly, the users can upload the data from their benchmarking experiments into the service for storing raw data. Furthermore, the service for calculating metrics can calculate metrics in a "off-line" manner, meaning that the whole experiment, defined with a set of ground truths and estimates (optionally also processing delays of location estimation and energy consumptions of the SUT), and the service will calculate and store the experiment results and performance metrics. Finally, the cloud service can be also used for interfacing the SUT, over the same API used in the testbed infrastructure.

III. RF Hardware Components

This section gives a short generic description of different types of RF hardware components that are part of the Telecommunication Network Group (TKN) infrastructure and are currently available for experimentation in the TKN testbed.

A. Deployment of SUTs and RF Interference Generation

Parts of our testbed infrastructure can be used as infrastructural nodes of the SUT or for generating RF interference, depending on the needs of an experiment. This section presents the indoor sensor testbed and a set of Wireless Fidelity (WiFi) Access Points (APs) and embedded Personal Computers (PCs) for that purpose. Finally, we present our signal generator, which can be used solely for the RF interference generation purpose.

a) TKN Wireless Indoor Sensor Network Testbed: The TKN Wireless Indoor Sensor Network Testbed (TWIST) [9] is a multiplatform, hierarchical testbed architecture developed at the TKN. The selfconfiguration capability, the use of hardware with standardized interfaces and open source software make the TWIST architecture scalable, affordable, and easily replicable. The TWIST instance at the TKN office building is one of the largest remotely accessible indoor sensor network testbeds with 204 sockets, currently populated with 102 eyesIFX and 102 Tmote Sky nodes (Figure 2). The nodes are deployed in a 3D grid spanning over 3 floors of an office building at the Technische Universität Berlin (TUB) campus, resulting in more than 1500 m^2 of instrumented office space. In small rooms, two nodes of each platform are deployed, while the larger ones have four nodes. This setup results in a fairly regular grid deployment pattern with intra node distance of 3 m, as shown in Figure 4. Within the rooms the sensor nodes are attached to the ceiling.

Fig. 2: Tmote Sky, eyes IFXv2, NLSU2 supernode/USB Hub

(a) Turtlebot 2 (b) TL-WDR4300 WLAN AP

Fig. 3: Hardware components of the testbed

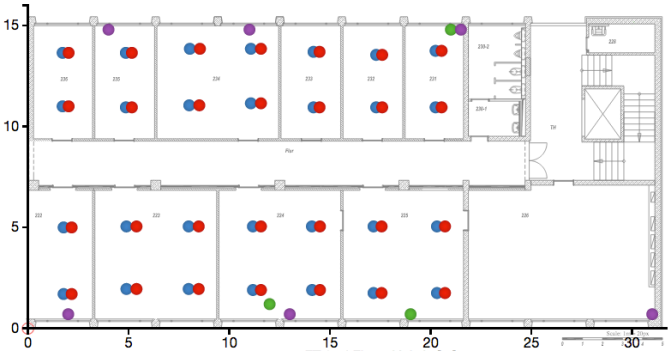


Fig. 4: Locations of the devices in the 2nd floor of the testbed (red: eyesIFX, blue: Tmote sky, purple: WLAN router, green: AlixD2D PC)

b) WiFi APs: TKN testbed is equipped with 18 dualband TP-link N750 APs (model TL-WDR4300) [10] (Figure 3b). They run OpenWRT as an Operating System (OS). Additionally to that we also have three ALIX2D2 embedded PCs [11] (Figure 5a) equipped with Broadcom WL5011S 802.11b/g cards. They are running Ubuntu as an OS. Both types of devices can be controlled by the cOntrol and Management

(a) Alix2D2 embedded PC (b) WiSpy dongle (c) R&S spectrum analyser (d) R&S signal generator

Fig. 5: Hardware components of the testbed

Framework (OMF). All of them can be configured as APs as well as WiFi clients, allowing the flexible and easy configuration of experiments. Positions of the WiFi APs and embedded PCs in the 2nd floor of TKN testbed are given in Figure 4.

c) R&S SMBV100A Signal Generator: Rhode&Schwarz SMBV100A is a very flexible signal generator [12] (Figure 5d). It provides transmissions of baseband signals in the range of 9 kHz to 6 GHz. It is possible send any generated or stored signal with up to 120 MHz bandwidth. By applying toolboxes, the SMBV100A signal generator allows generating different standards conform signals like e.g., WiMAX, WiFi or Long Term Evolution (LTE). Together with the R&S FSV7 Spectrum Analyzer complete transmission chains can be set.

B. RF Interference Monitoring

For the purpose of monitoring the uncontrolled and controlling the generation of controlled RF interference our testbed infrastructure leverages two types of spectrum monitoring devices.

a) Low-Cost Spectrum Analyzers: The TKN infrastructure also comprises several WiSpy sensing devices (Figure 5b). These are low-cost spectrum scanners that monitor activity in either 868 MHz, 2.4 GHz or 5 GHz spectrum, and output the measured RF energy of the received signals. They can be attached, via USB port, to any PC in the testbed.

b) R&S FSV7 Spectrum Analyzer: Rhode&Schwarz FSV7 signal and spectrum analyzer [13] (Figure 5c) is a very flexible and fast signal and spectrum analyzer covering the frequency range between 9kHz and 7 GHz. It is simple extensible by several measurement applications and toolboxes. Furthermore, it is possible, by buying appropriate licenses, to add complete receiver chains like Bluetooth, LTE, WiMAX or WiFi.

IV. Autonomous Mobility Platform

The static TKN testbed environment has been enriched with mobile robotic platforms, to allow experiments where dynamic changes of locations are needed. Those mobile robotic platforms are based on an open source hardware and software development called Turtlebot-II [14] and have been further enhanced to fit our testbed environment seamlessly. They consist of a mobile base (Kobuki), a laptop and a Microsoft Kinect 3D camera, as well as optional Light Detection and Ranging (LIDAR) sensor (Figure 3a). The basic functionality of the platform allows autonomous localization and navigation with dynamic obstacle avoidance inside buildings by leveraging a provided floor plan and combining it with depth readings from the visual sensor. Obstacle avoidance is being a crucial property when the mobile robotic platforms operate in a non-controlled office environment. Our enhancements, besides multiple minor adaptations to enable a fully autonomous operation within our testbed, include equipping the mobile platforms with high-performance WiFi routers that automatically monitor, select and connect to the best possible WiFi AP available. This is shown in Figure 6, depicting the usage of different APs based on the position of the robotic platform on the 2nd floor of the TKN environment, in order to achieve seamless connectivity of the robot in the environment. The robot APs operate in 5 GHz ISM frequency band, in order to be out-of-band to the indoor localization SUTs to avoid interfering with it.

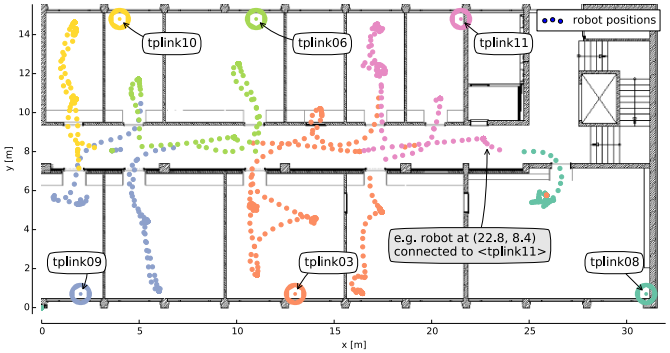


Fig. 6: Automatic switching of APs based on the location of the autonomous mobility platform

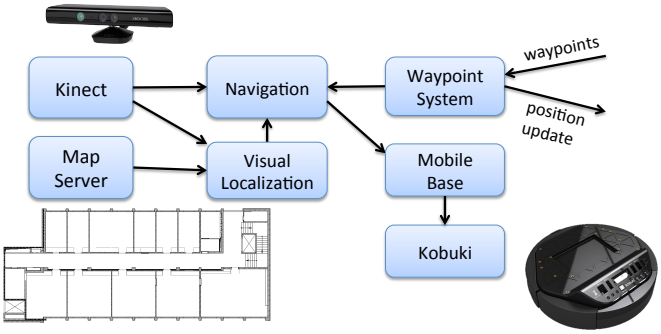


Fig. 7: Design of the robotic platform

A. Accuracy of Autonomous Mobility Platform

In our testbed infrastructure we consider the location estimates provided by the autonomous mobility platform as the ground truth for indoor localization benchmarking experiments. To be able to use this information in that way, we needed to make sure that the accuracy of the autonomous

mobility platform is at least one order of magnitude higher than the usual performance of the RF-based indoor localization solutions. Due to that, we have evaluated the accuracy of our platform in two different settings. The first evaluation scenario was during the Microsoft Indoor Localization Competition in conjunction with International Conference on Information Processing in Sensor Networks 2014 (IPSN'14). The competition was performed in the the area with the size of around 200 m^2, consisting of two big conference rooms and a hallway. Overall 20 evaluation point were defined, labeled on the floor and their coordinates were manually measured. Following that, we used our mobility platform to position itself on each defined point, and measured the errors using the laser distance measuring device. The average localization error of the mobility platform in this environment is less than 25 cm. Further, we performed the similar experiment in our testbed. Involving a sophisticated device Tachymeter Typ TS 06 Plus (Leica) [15], with the accuracy of 2 mm at 100 m, we defined a set of 28 points in our testbed environment. We navigated the mobility platform to each of them and measured the positioning errors with the laser distance measuring device. The accuracy of our autonomous mobility platform in this environment is even better, achieving the overall mean accuracy of less than 15 cm. The reason for better accuracy in this environment is better accuracy of the internal map of the robot, optimization of the internal parameters of the robot (e.g. improved navigation and dead-reckoning) and a very challenging set-up of the IPSN'14 environment. The Cumulative Distribution Function (CDF) of the localization errors in both experiments are given in Figure 8, while the summarized performance results are given in Table I.

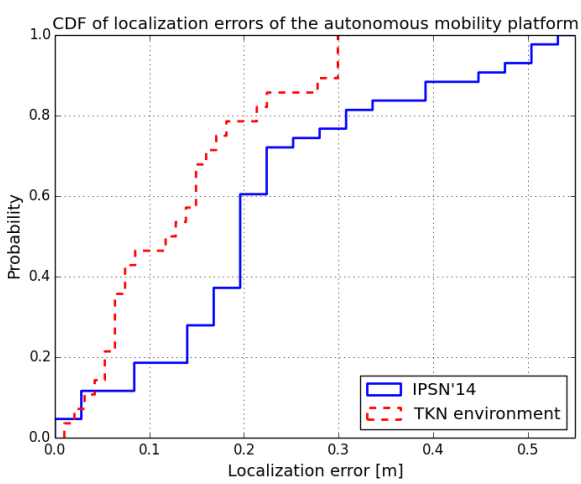


Fig. 8: CDFs of the localization errors of the robotic platform in two environments

TABLE I: Summary results of the accuracy of robotic platform in two environments

Metrics	IPSN'14	TKN environment
Mean loc. error [m]	0.234	0.142
Loc. error variance [m^2]	0.018	0.015
Loc. error median [m]	0.221	0.136
Min/max loc. error [m]	0.000 / 0.560	0.010 / 0.310

V. Testbed Infrastructure for Supporting Indoor Localization Benchmarking

This section presents the components of our testbed infrastructure for supporting indoor localization benchmarking. The overview of the system is given in Figure 9. Below in text we separately discuss each of functional components of the testbed.

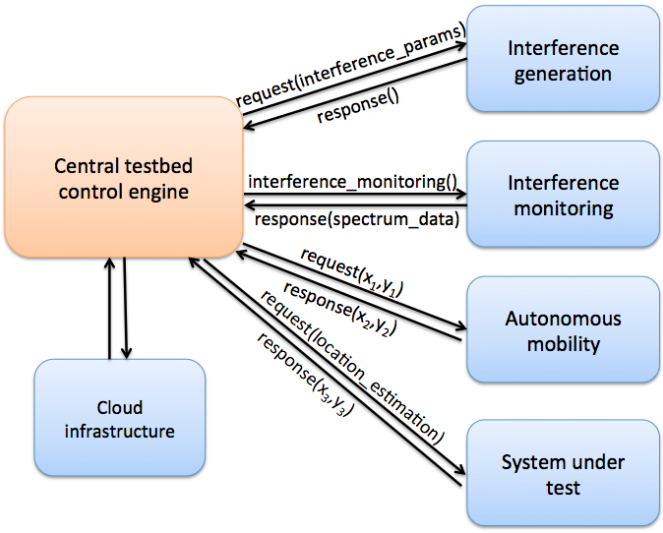


Fig. 9: Overview of the benchmarking system

a) Central Testbed Control Engine: Central testbed control engine is used for instrumenting other functional components of the testbed: interference generation and monitoring, autonomous positioning of the SUT using the autonomous mobility platform and interfacing the SUT. In other words, central testbed control engine is nothing more than a set of scripts that can be used for starting RF interference on the devices for generating interference or start monitoring the wireless spectrum on the devices envisioned for spectrum monitoring. Further, central control engine is used for autonomous navigation of the robotic platform and SUT to the evaluation points, requesting estimates from the SUT and sending the estimates and the raw data for further processing and storage in the cloud infrastructure.

b) Location Estimation Requests: In our benchmarking experiments, the indoor localization SUT is considered a black-box solution and the only requirement for the SUT is to be able to report the estimated location on request using the standard Hypertext Transfer Protocol (HTTP) requests. The only necessary interaction with the SUT, performed over a well defined API, is used to obtain location estimates. Namely, the API is the HTTP Uniform Resource Identifier (URI) on which the SUT listens for requests for location estimation. Upon request, the SUT has to provide the location estimate as a JavaScript Object Notation (JSON) response in the following format:

```
{"coordinate_x": 'Estimated location: coordinate x',
 "coordinate_y": 'Estimated location: coordinate y',
 "coordinate_z": 'Estimated location: coordinate z',
 "room_label":   'Estimated location: room'}
```

JSON parameters *coordinate_x* and *coordinate_y* are x and y coordinates of the estimated location. These coordinates are expressed in meters and are relative to the zero-point in the testbed, with coordinates $(x, y, z) = (0, 0, 0)$, as presented in Figure 4, where the same zero-point is used by the autonomous mobility platform. They are required parameters and as such they must be reported upon request. Parameter *coordinate_z*, also expressed in meters, is an optional parameter, due to the 2D evaluation environment. Finally, parameter *room_label* defines the room label in which the SUT estimates it is.

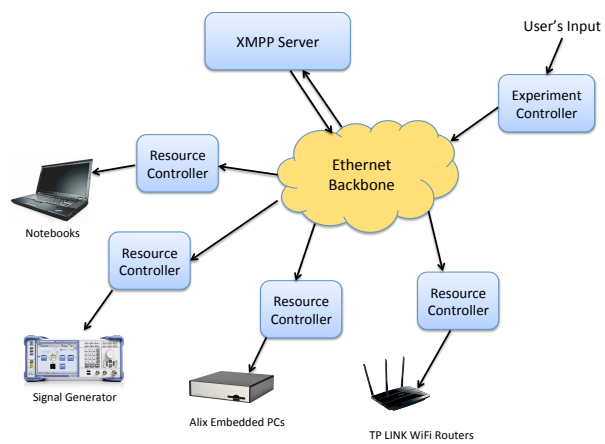
Combined with reference location data from the robotic mobility platform, the obtained location estimates are subsequently processed by a dedicated cloud engine that calculates relevant evaluation metrics like geometrical and room level accuracy and latency, which is discussed in the following section of the paper.

c) Mobility Support: The autonomous mobility platform (as described in Chapter IV) can be used for transportation of the SUT to different localization evaluation points, without the presence of a human test-person and in a repeatable way. It provides a simple interface, named *Waypoint Controller*, to request the robot to drive autonomously to a given coordinate, as shown in Figure 7. For an experiment, we define a set of measurement points. The robot then iterates autonomously over each one of them, computing a shortest path to each goal using the internal navigation system, as well as taking dynamic obstacles into account. Upon reaching a measurement point, the testbed's control engine requests the estimated location from the SUT. After the SUT reports the localization results, the robot is requested to proceed with the next evaluation point.

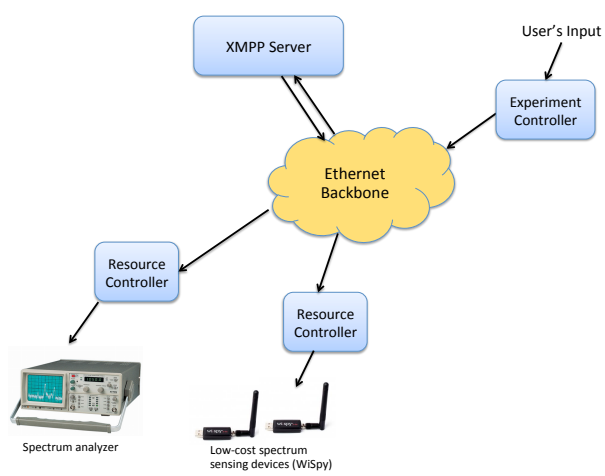
d) Interference Generation: RF interference can have an impact on the performance of the RF-based indoor localization solutions. In order to evaluate this impact we have developed means to generate various types of interference scenarios, varying on the technology, strength or usage patterns. We can separate those in three main parts, namely: based on WiFi traffic, low-power sensor nodes traffic and arbitrary signal as the interference pattern.

A common type of wireless activity in the 2.4 GHz ISM band is WiFi traffic. We have adapted the interference scenarios from [16], [17] and, with help of the OMF [18] orchestrating the wireless routers and embedded PCs, we can create the interference context of typical home or office environments. As shown on Figure 10a we are using cabled backbone to control all devices participating in the interference generation. Furthermore, using distributed low-power sensor nodes provided by TWIST we can generate various types of IEEE 802.15.4 traffic patterns or constant carrier (jamming) as interference sources. Finally, using the signal generator we are able to generate power envelopes of any periodic signal with Arbitrary Waveform Generator (ARB) provided by the device. This includes IEEE 802.11 (WiFi), IEEE 802.15 (Bluetooth), but also synthetic interference such as microwave or Digital Enhanced Cordless Telecommunications (DECT). When using our prepared signals, it is possible to control the signal generator with OMF which reduces the knowledge required to use them device, thus simplifies the experimentation.

e) Interference Monitoring: In the text above we have described the generation of different interference scenarios based on the needs of an experiment. Due to the fact that 2.4 GHz ISM spectrum band is free for the usage, the uncontrolled RF interference can be expected. For this and in order to control if the intended interference is generated in a desired way, it is necessary to monitor the wireless spectrum. We use OMF to orchestrate WiSpy [19] devices to perform spectrum sensing in the different locations in the testbed. Also, one WiSpy device is attached to the autonomous mobility platform, to make sure that the measured interference is not exceeding the planned one at each evaluation point. Finally, for a fine-resolution monitoring of the spectrum we can use the high-end spectrum analyzer device. This device can also be orchestrated using OMF, as shown in Figure 10b, which reduces the complexity of usage of such device. Some RF localization solutions can also impact the standard WiFi operation. With the monitoring system and mechanisms built-in the interference generation it is possible to detect and quantify such an impact.



(a) Interference generation system



(b) Interference monitoring system

Fig. 10: Interference generation and monitoring systems

VI. Cloud Services for Supporting Indoor Localization Benchmarking

The functions of the cloud infrastructure for benchmarking of indoor localization are the following: storing the raw data of indoor localization benchmarking experiments, storing the results of indoor localization experiments and calculation of the metrics characterizing the performance of RF-based indoor localization solutions.

The envisioned cloud infrastructure for indoor localization benchmarking is presented in Figure 11. Given the information about ground truth location, central engine can request raw data or location estimate from the indoor localization SUT, using the same API as described previously. Central engine can then store the raw data into the raw data storage service [20], together with the information about ground truth location, i.e. the location where a measurement was taken, and the time needed to collect the data. Further, central engine can store the location estimate, together with the ground truth, into the service for storing the results of benchmarking experiments. Moreover, central engine can calculate metrics from the obtained location estimates [21]. Metrics that can be calculated are geometrical and room level accuracy, latency of indoor localization and energy consumption, which are detected as the relevant metrics for characterizing the performance of RF-based indoor localization in our previous work [8]. Central engine communicates with the SUT over HTTP protocol. The minimum requirement for the SUT is to provide the location estimation when requested. Finally, in order to be able to store the raw data, i.e. the data that SUT internally uses for localization purposes, SUT should also provide it when requested.

Central engine stores the raw data into the raw data storage service. If needed, raw data can then be used by the SUT for the further location estimation. For example, in fingerprinting based indoor localization the whole training dataset can be stored into the raw data storage service, and then can be used again by the SUT for further location estimation. The processed data, i.e. benchmarking results, are stored in the web service for storing the results of benchmarking experiments.

The central engine is implemented as a tuple of Remote Procedure Calls (RPCs), namely for *offline* and *online* calculation of performance metrics of indoor localization benchmarking experiments. The message definition and serialization format is Protocol Buffer [22]. Namely, for the *offline* calculation of performance metrics user can define a message consisting of a set of ground truth locations and corresponding estimates, together with latencies of the SUT needed to provide these estimates, and send them to the central engine. The engine will then reply with the performance metrics and, if requested, store the whole experiment into the benchmarking results database. Similarly, for the *online* calculation of performance metrics user can define a message consisting of only one ground truth location where the measurement was taken, estimate location given at that measurement point and the latency needed to provide the estimate. When the message is sent

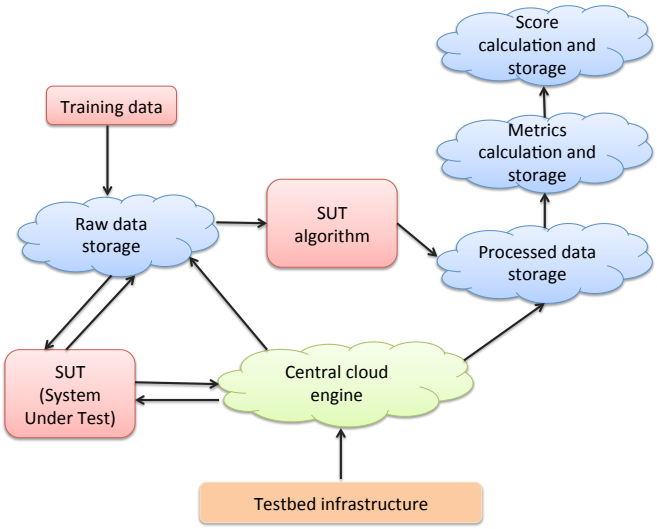


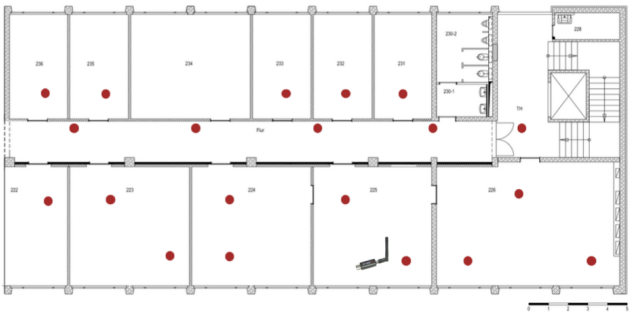
Fig. 11: Overview of the cloud infrastructure

to the central engine, the engine will automatically update the corresponding database with a given evaluation point, reply with the calculated evaluation metrics and store the data. A detailed description of message formats, defined procedures and usage of the central engine is given in [21].

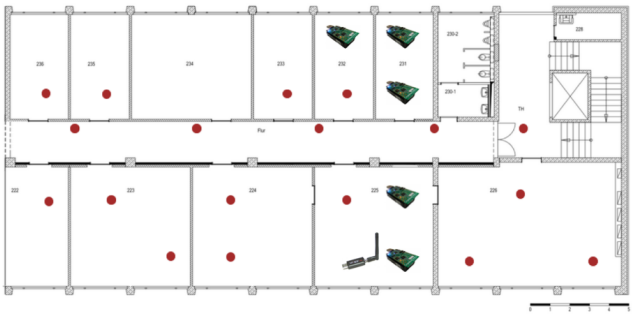
The services for storing raw data and benchmarking results of indoor localization benchmarking experiments are developed as the RESTful APIs. The message definition and serialization format is again Protocol Buffer, where for each service different message can be used. The raw data storage service uses the message that defines the usual types of raw data used in RF-based indoor localization, such as Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), Angle of Arrival (AoA) and Link Quality Information (LQI). This set or data can be easily extended, which is a feature of Protocol Buffer format. The data is stored with the ground truth location where the measurement was taken and the time needed to obtain the measurement. Similarly, the message containing the results of benchmarking experiments is defined with the set of evaluation points, each containing the ground truth, corresponding location estimate and time needed by the evaluated SUT to produce it. Further, message also contains the metrics characterizing the performance of the SUT in the whole experiment stored in the database. Further details about the messages types and usage of both services is given in [20].

VII. Example Usage

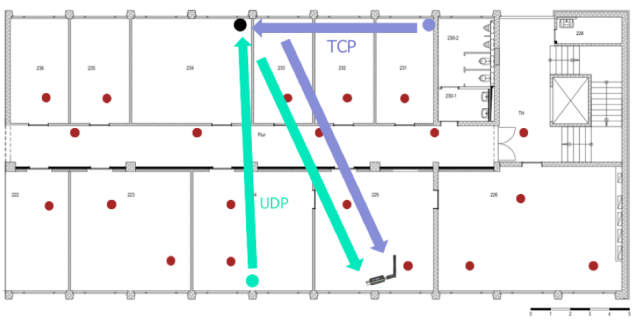
As an example of using the testbed and cloud infrastructure we present a set of experiments with controlled interference in which we benchmark an example WiFi-based fingerprinting solution in details presented in [23]. For generating fingerprints this solution uses the quantiles of RSSI values from beacon packets transmitted from multiple WiFi APs in the testbed premises. Furthermore, the solution uses Pompeiu-Hausdorff distance for calculating the difference between training fingerprints and ones generated by user to be localized. Finally, the solution uses the k-Nearest Neighbors (kNN) procedure with



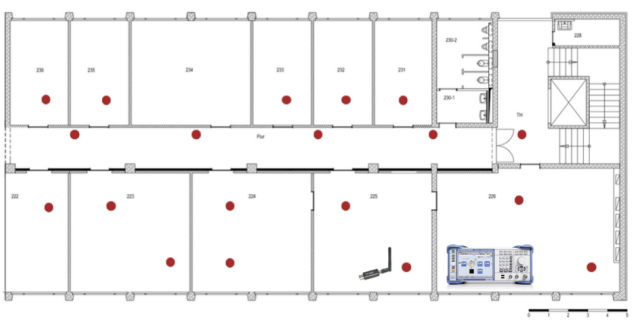
(a) Reference scenario



(b) Interference scenario 1



(c) Interference scenario 2



(d) Interference scenario 3

Fig. 12: Locations of the evaluation points, interferers and spectrum monitoring devices in all scenarios

the parameter k set to 4.

Apart from the example we present here, part of our infrastructure, namely the robotic platform for positioning SUTs devices and cloud services for metrics calculation and storage, has already been used in the IPSN / Microsoft Indoor Localization Competition [24]. Furthermore, the full possibilities of our infrastructure have been used in the Track 3 of the EVARILOS Open Challenge, as described in [7], [25]. Namely, a number of competitors used our infrastructure remotely in order to deploy their algorithms on top of the already existing hardware. A variety of algorithms has been successfully deployed and benchmarked, ranging from ToF-based multilateration to RSSI-based proximity and fingerprinting. The performance of each solution has been evaluated in four interference scenarios, showing that RF interference has an impact on all evaluated solutions. The experiment results together with metrics are available at:

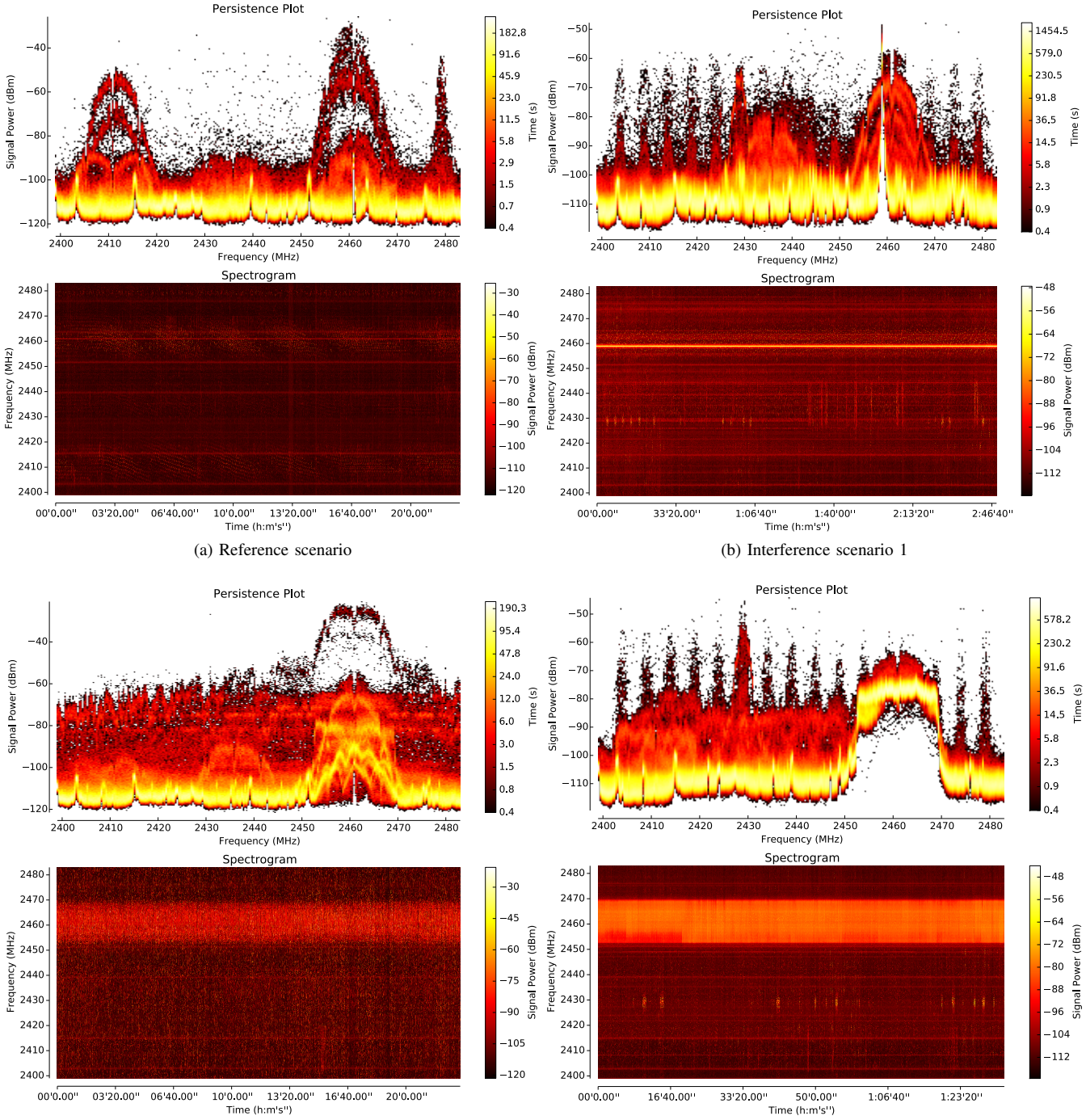
http://ebp.evarilos.eu:5011/

As an example, here we present the performance of the SUT that was evaluated in four scenarios, namely reference and three different interference scenarios. The autonomous mobility platform was used to position the evaluated SUT on the same evaluation points in all scenarios, where the locations of evaluation points are given with red dots in Figure 12. In all four scenarios the 2.4 GHz wireless spectrum was monitored using two WiSpy devices, one mounted on the robot and the other at the location given in Figure 12. The interference monitoring output of the WiSpy device with the location given in Figure 12 for all four scenarios is given in Figure 13. For each scenario the figure depicts firstly a persistence plot, showing the measured power in dBm on each frequency, where the different colors show for how long a given power was observed at particular frequency. The second plot shows the spectrogram plot, presenting the signal power measured for each frequency over the duration of the whole experiment.

TABLE II: Primary metrics summary

Metric	Reference scenario	Interference scenario 1	Interference scenario 2	Interference scenario 3
Mean loc. error [m]	2.82	5.20	3.84	4.02
Median loc error [m]	2.61	4.81	3.11	3.56
RMS loc. error [m]	3.14	5.88	4.75	4.80
75 percentile loc. error [m]	3.87	6.46	5.14	5.36
90 percentile loc. error [m]	4.19	9.49	5.87	7.37
Min. loc. error [m]	0.47	0.88	1.26	0.79
Max. loc. error [m]	5.76	11.46	13.70	10.93
Room level acc. [%]	70.00	45.00	40.00	45.00
Mean latency [s]	20.08	20.58	19.88	20.02
Median latency [s]	20.05	20.45	19.83	20.05
RMS latency [s]	20.09	20.58	19.88	20.02
75 percentile latency [s]	20.11	20.71	19.95	20.11
90 percentile latency [s]	20.25	21.64	20.03	20.16
Min. latency [s]	19.66	19.92	19.71	19.67
Max. latency [s]	21.02	21.94	20.11	20.26

In the reference scenario no controlled interference was generated, so the results of this scenario give the baseline performance of the evaluated SUT. The first interference scenario was using 5 low-power sensor nodes for jamming



(a) Reference scenario

(b) Interference scenario 1

(c) Interference scenario 2

(d) Interference scenario 3

Fig. 13: Spectrum information for all scenarios

on one IEEE 802.15.4 channel. The locations of jammers are given in Figure 12b, while the spectrum seen by the WiSpy device at the location given in the same figure is given in Figure 13b. In the interference scenario 2 the usual home or office WiFi traffic was generated as the interference source, as shown in Figure 12c. The 2.4 GHz wireless spectrum was again monitored with the WiSpy device, as shown in Figure 13c. Finally, in the interference scenario 3 we used signal generator on the location given in Figure 12d, and generated a power envelope of a WiFi traffic, which could be considered as jamming on one WiFi channel. The spectrum was monitored and the results are shown in Figure 13d.

The location estimates were requested from the SUT device and together with ground truths and latencies of producing location estimates sequentially sent to the cloud services. There the metrics were calculated and the results were stored in the database for storing the results of benchmarking experiments. Finally, the summarized results are presented in

Table II. As seen in the table, the summarized results of the experiments are extensive statistics regarding point and room accuracy of indoor localization and the latency of providing the location estimates. Also, it is visible from the table that the performance of the evaluated SUT is reduced, in terms of the point and room level accuracy, in the interference scenarios in comparison to the reference. This fact hints that RF interference can have an influence to RF-based indoor localization, which is yet to be examined.

VIII. Conclusion

This work presented the testbed and cloud infrastructure for evaluation end benchmarking of RF-based indoor localization solutions in the environments with artificially generated RF interference. Using the proposed infrastructure gives the possibility of repeatable and comparable benchmarking, removing the need for a test-person. Further, the results of benchmarking experiments are presented in a unified way, with a set or relevant metrics following the extensive benchmarking methodology developed as the part of the EVARILOS project. The raw data from the experiments, as well as the results, are publicly available, meaning people are able to evaluate the performance of newly developed solutions on the same data, without even performing the testbed experiments, and compare their results with the performance of already benchmarked solutions. Finally, as the proof of concept we presented the benchmarking experiments with controlled RF interference, performed using a WiFi fingerprinting solution as an example SUT. Our example shows how indeed the infrastructure is feasible for performing the benchmarking experiments without or with controlled RF interference. Finally, our experiments indicate that RF interference indeed influences the performance of the example indoor localization solution.

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References

[1] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan, "Indoor localization without the pain," in *Proceedings of the sixteenth annual international conference on Mobile computing and networking*, ACM, 2010, pp. 173–184.

[2] J. Yang and Y. Chen, "Indoor localization using improved rss-based lateration methods," in *Global Telecommunications Conference, 2009. GLOBECOM 2009. IEEE*, IEEE, 2009, pp. 1–6.

[3] M. S. Bargh and R. de Groote, "Indoor localization based on response rate of bluetooth inquiries," in *Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments*, ACM, 2008, pp. 49–54.

[4] F. Lemic, V. Handziski, A. Behboodi, A. Wolisz, N. Wirstrm, T. Voigt, T. Van Haute, and E. De Poorter, "Report on Experiments With Controlled Interference," in *EVARILOS Project Deliverable*, 2014.

[5] T. Van Haute *et al.*, "D2. 1 Initial Version of the EVARILOS Benchmarking Handbook," 2013.

[6] F. Lemic, J. Büsch, M. Chwalisz, V. Handziski, and A. Wolisz, "Demo Abstract: Testbed Infrastructure for Benchmarking RF-based Indoor Localization Solutions under Controlled Interference," in *EWSN'14, University of Oxford, Oxford, UK*, 2014.

[7] F. Lemic *et al.*, "EVARILOS Open Challenge - Track 3," in *EVARILOS Project Deliverable*, 2014.

[8] T. V. Haute *et al.*, "The EVARILOS Benchmarking Handbook: Evaluation of RF-based Indoor Localization Solutions," in *MERMAT 2013*, May 2013.

[9] V. Handziski, A. Köpke, A. Willig, and A. Wolisz, "TWIST: a scalable and reconfigurable testbed for wireless indoor experiments with sensor network," in *Proc. of the 2nd Intl. Workshop on Multi-hop Ad Hoc Networks: from Theory to Reality, (RealMAN 2006)*, 2006.

[10] *N750 Dualband WLAN Router*, Available at http://www.tp-link.com.de/products/?categoryid=2166, 2013.

[11] *Alix2D2*, Available at http://www.pcengines.ch/alix2d2.htm, 2013.

[12] *R&S SMBV100A Vector Signal Generator*, Available at http://www.rohde-schwarz.de/de/Produkte/messtechnik-testsysteme/signalgeneratoren/SMBV100A.html, 2013.

[13] *R&S FSV7 Signal Analyzer*, Available at http://www.rohde-schwarz.de/de/Produkte/messtechnik-testsysteme/signal-und-spektrumanalysatoren.html, 2013.

[14] *Turtlebot II Documentation*, 2013. [Online]. Available: http://wiki.ros.org/Robots/TurtleBot.

[15] *Leica FlexLine TS06*, 2014. [Online]. Available: http://www.surveyequipment.com/PDFs/Leica_FlexLine_UserManual.pdf/.

[16] W. Liu, M. Mehari, S. Bouckaert, L. Tytgat, I. Moerman, and P. Demeester, "Demo Abstract: A Proof of Concept Implementation for Cognitive Wireless Sensor Network on a Large-scale Wireless Testbed," in *EWSN'13*, 2013.

[17] *CREW repository*, 2013. [Online]. Available: http://www.crew-project.eu/repository/.

[18] *OMF 6 Documentation*, 2013. [Online]. Available: http://omf.mytestbed.net/projects/omf6/wiki/Wiki.

[19] *Metageek Wi-Spy*, 2013. [Online]. Available: http://www.metageek.net/products/wi-spy/.

[20] F. Lemic and V. Handziski, "Data Management Services for Evaluation of RF-based Indoor Localization," Telecommunication Networks Group, Technische Universität Berlin, Tech. Rep. TKN-14-002, 2014.

[21] F. Lemic, "Service for Calculation of Performance Metrics of Indoor Localization Benchmarking Experiments," Telecommunication Networks Group, Technische Universität Berlin, Tech. Rep. TKN-14-003, 2014.

[22] *Google's Protocol Buffers*, 2013. [Online]. Available: https://code.google.com/p/protobuf/.

[23] F. Lemic, "Benchmarking of Quantile based Indoor Fingerprinting Algorithm," Telecommunication Networks Group, Technische Universität Berlin, Tech. Rep. TKN-14-001, 2014.

[24] D. Lymberopoulos, J. Liu, X. Yang, R. R. Choudhury, S. Sen, and V. Handziski, "Microsoft Indoor Localization Competition: Experiences and Lessons Learned," in *SIGMOBILE Mobile Computation and Communication Review (MC2R)*, To appear, SIGMOBILE, 2014.

[25] F. Lemic and others, "EVARILOS Open Challenge: Track 3," Telecommunication Networks Group, Technische Universität Berlin, Tech. Rep. TKN-14-005, 2014.