2012 International Conference on Indoor Positioning and Indoor Navigation, 13-15th November 2012

Indoor localization with UMTS compared to WLAN

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***Abstract*—The objective of this paper is to compare the accuracy in location estimation which can be achieved in an indoor-scenario for WLAN and UMTS using RF-Fingerprinting with various metrics and distance norms.**

The measurements were done in a $20\,\mathrm{m}$ x $15\,\mathrm{m}$ office environment, using 4 3G Small Cells (Home NodeB) and 4 WLAN-APs. To create the radio map, fingerprints were taken within a grid of one meter. For location estimation a deterministic approach using Euclidean Distance norm with a WKNN algorithm was used based on RSS and AP-visibility as metrics. As a probabilistic approach a histogram comparison method has been applied using Kullback-Leibler-Divergence as a distance norm.

It can be shown, that the accuracy in Indoor-RF-Fingerprinting with UMTS is comparable to the accuracy, which can be achieved in a similar WLAN-Testbed. Signal visibility is an alternative metric to RSS for interference limited systems, such as UMTS.

As a conclusion UMTS Small Cells are an interesting alternative to WLAN for indoor RF-Fingerprinting, especially because the same hardware can be used for traffic and for localization purposes, since the pilot is not subjected to adaptive frequency hopping or power control, as it is the case in most WLAN installations for interference reduction.

I. Introduction

RF-Fingerprinting for indoor localization has frequently been investigated in wireless systems such as WLAN [1], [2]. RF-Fingerprinting in cellular systems such as GSM or UMTS has rather been analyzed in outdoor environments to support poor GPS signals [3]. With the availability of Small Cells for indoor coverage, UMTS based RF-Fingerprinting could be an alternative or complementary to a WLAN based solution using smartphones to display location information.

UMTS Small Cells have already been used for indoor localization in related works using a Rake Estimator, which carries out correlation of the received signal with delayed paths [4]. However these TOA based channel estimators suffer from noise and near-far effects, yielding in localization accuracies above room level [5]. With WLAN RF-Fingerprinting better accuracies below room level can be achieved [6]. It is therefore the objective of this work to elaborate if these results can also be achieved, when using Fingerprinting with Small Cells in UMTS-FDD mode.

Since UMTS bandwidth is only $5\,\mathrm{MHz}$ compared to $20\,\mathrm{MHz}$ in case of WLAN, more significant small-scale fading can be expected. Furthermore UMTS is an interference limited system and accordingly the fingerprints of distant neighbor cells have not the same visibility as in a comparable WLAN installation. On the other hand UMTS cellular phones are using a Rake-Receiver, which takes advantage from multipath propagation and radio measurement reports are updated more frequently when the UE is in "connected mode". These aspects motivated us to analyze more deeply the performance of indoor RF-Fingerprinting using UMTS Small Cells.

In this work, we are comparing the performance of UMTS versus WLAN in a $20\,\mathrm{m}$ x $15\,\mathrm{m}$ office environment using 4 Small Cells and 4 WLAN-APs. Fingerprints have been taken within a grid of $1\,\mathrm{m}$ using AP visibility and RSS as a metric. For the metric visibility a threshold had to be calibrated in order to optimize the performance. As a deterministic distance norm we used the Euclidean distance, while we were using a histogram comparison method with KL Divergence as a stochastic norm, as already proposed in [2] and [7]. In both cases a weighted k nearest neighbor algorithm (WKNN) was applied for position estimation. Since the measurements were taken under static conditions no further filtering such as Kalman Filter was necessary.

In Chapter II the methods to estimate the position of the mobile client are described by specifying the metrics, distance norms and algorithms which have been used. Chapter III gives an overview on the experimental setup, presenting the hardware for the UMTS and WLAN testbed as well as the WIPoS Toolchain, which has been used for the analysis. The measurements and results are shown and discussed in chapter IV. Chapter V summarizes the results, conclusions and provides an outlook to our future work.

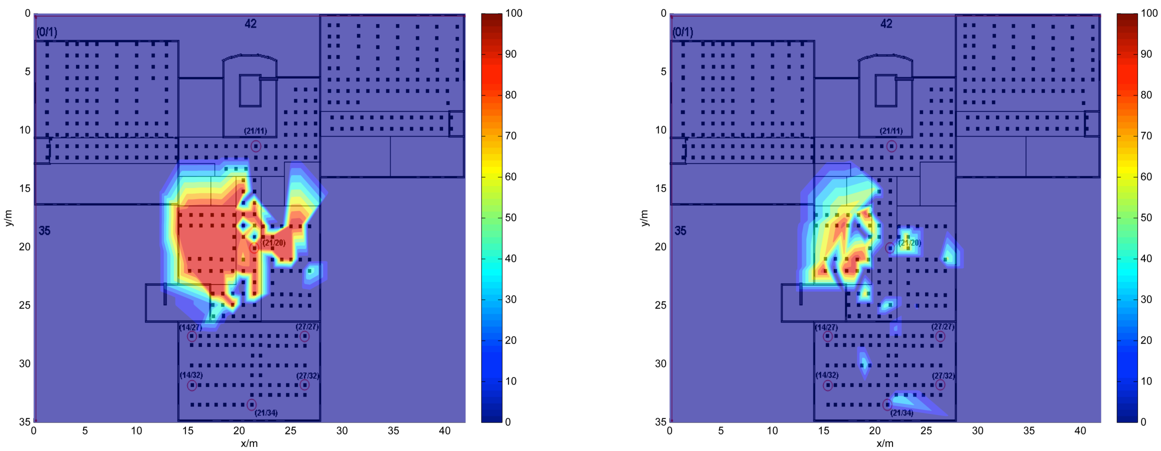
II. Location estimation methods

The user's position is estimated during the online phase by comparing a measured location dependent metric to a previous calibrated radio-map. This radio-map contains the so called Fingerprints at predefined calibration points, which need to be collected for a specific period of time depending on the update rate of the metric. The calibration points, whose metrics have the smallest distance to the current measurement, are used to estimate the position.

The metrics, distance norms and localization method which has been used in this work for position estimation are described in the following subsections.

A. Metrics: RSS and AP visibility

1) RSS: received signal strengths: The received signal strength (RSS) is the most common metric used for RF-Fingerprinting. In case of WLAN, the downlink RSS finger-



(a) WLAN Visibility Ant7 ($AP_{th} = -55\,\mathrm{dBm}$) (b) UMTS Visibility SC20 ($AP_{th} = -80\,\mathrm{dBm}$)

Fig. 1. AP and SC coverage probability in [%] based on visibility metric

prints of the beacon were collected using passive scanning mode: Even though the beacon interval of the WLAN AP is 100msec, most Network Interface Cards (NIC) update the measured RSS only every 2s to 6s, because all channels are scanned consecutively in passive scanning mode [8].

UMTS measurement reports and thus updated CPICH RSCP fingerprints of visible Small Cells were available every 100ms (connected mode), when using a commercial UMTS Tracemobile.

In both cases the k minimum distances between the observed signal strength (RSS) vector $s_i = \begin{bmatrix} s_1 & s_2 & \cdots & s_n \end{bmatrix}$ and the RSS vector in the radio-map $S_i = \begin{bmatrix} S_1 & S_2 & \cdots & S_n \end{bmatrix}$ were computed by using the distance norms as described in subsection B.

Note: For a better readability we will use in the following sections the terms RSS (received signal strength) and AP (Access Point) instead of CPICH RSCP (received signal code power of the common pilot channel) and Small Cell also for UMTS.

2) AP visibility: We propose a metric, which is defined as the visibility of an AP in percent, when measuring a predefined amount of RSS samples. The decision if an AP is visible or not is defined by a calibrated threshold AP_{th} which turned out to be $-55\,\mathrm{dBm}$ for WiFi and $-80\,\mathrm{dBm}$ for UMTS giving the best position estimates. Accordingly AP visibility is defined as the local coverage propability

$$P_{cov} = prob(s_i > AP_{th}) \tag{1}$$

as shown in figure 1. $P_{cov} = 80\%$ means, that 80% of the measured RSS samples were larger than the calibrated threshold of $-55\,\mathrm{dBm}$ (figure 1(a)). A similar metric has already been used in [7].

B. Distance-Norms: Deterministic and Probabilistic Approach

1) Deterministic Approach: As a deterministic distance norm the Euclidean norm was used to calculate the k minimum signal distances between two vectors. Depending of the metric, the vectors either describe mean signal strengths (RSS) or AP availability in percent. This norm d_q is defined accordingly by

$$d_q = \left(\sum_{i=1}^{n} |s_i - S_i|^q \right)^{\frac{1}{q}} \tag{2}$$

with $q = 2$ [2].

2) Probabilistic Approach: Instead of taking the means out of several signal strength values, the probability distributions of the received signal strength can be compared by using the Kullback-Leibler (KL) divergence as a stochastic density distance measure. For probability distributions "P" and "Q" of a discrete random variable (RSS values of APs) their KL-divergence is defined to be

$$D_{\mathrm{KL}}(P\|Q) = \sum_i P(i) \ln \frac{P(i)}{Q(i)} \tag{3}$$

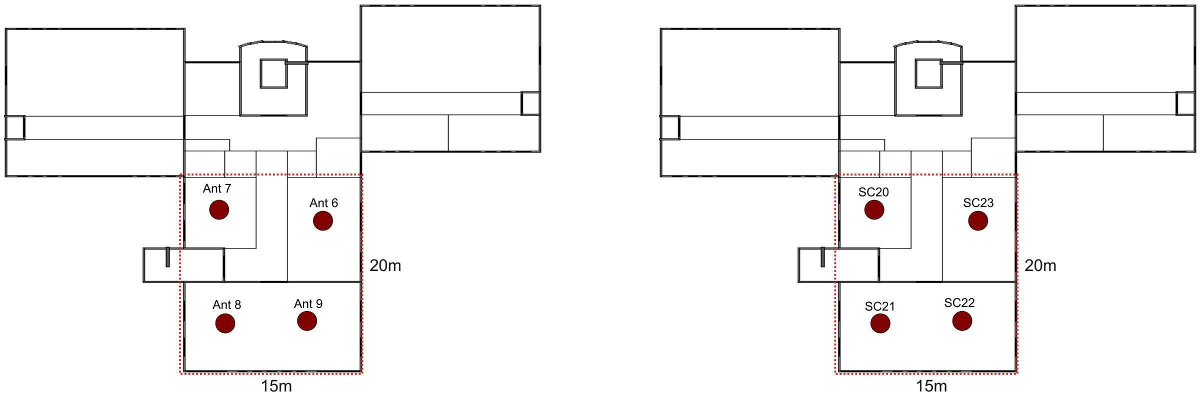
where P represents the reference distribution of data $P = S_i$ (collected during the offline phase). The measure Q represents the observed data at a unknown location ($Q = s_i$). To avoid taking logarithms of zero-valued bins, we added a small constant term of 10^{-6} as already proposed in [7]. Since the K-L Divergence is not symmetric the symmetrized Kullback-Leibler divergence $D_{KL,sym}$ between the two distributions S_i and s_i has been used, which is defined as

$$D_{\mathrm{KL,sym}}(S_i, s_i) = D_{\mathrm{KL}}(S_i\|s_i) + D_{\mathrm{KL}}(s_i\|S_i) \tag{4}$$

With $p = P(S|\{x, y\})$ expressing the RSS distribution at each position in the reference database and $q_u = Q(s|\{x_u, y_u\})$ the RSS distribution of an unknown position we therefore have for any two locations $\{x, y\}$ and $\{x_u, y_u\}$ and for J access points [7]:

$$D(p, q_u) = \sum_{j=1}^{J} D_{\mathrm{KL,sym}}(P_j(S|\{x, y\}), Q_j(s|\{x_u, y_u\})) \tag{5}$$

To encode the RSS distributions we used a bin size of $5\,\mathrm{dB}$.



(a) WLAN AP position

(b) Small Cell Postions

Fig. 2. WLAN and UMTS setup

C. Localization Method

For the position estimates the weighted K-Nearest-Neighbor algorithm (WKNN) [2], [9] was used. The neighbors are computed by finding the k minimum signal distances by using the metrics and distance norms as described above. Because the measurements have been performed under static conditions, no further filtering such as Kalman filter was used.

III. Experimental Setup

A. WLAN and UMTS Setup

For the testbed an area of $20\,\mathrm{m}$ x $15\,\mathrm{m}$ was selected in a public building of the university campus. 4 WLAN-APs and 4 Small Cells were installed onto the ceiling (figure 2). The 4 WLAN APs (Ant6 to Ant 9) were commercially available access points (Linksys WRT54GL) with a specific firmware (OpenWRT) operating on the same channel (channel 13, $2472\,\mathrm{MHz}$) with an antenna gain of $2\,\mathrm{dBi}$ and transmitting power of $20\,\mathrm{dBm}$ (figure2).

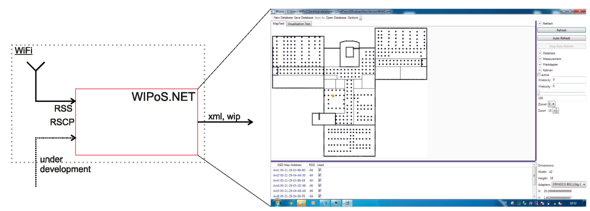
The 4 UMTS Small Cells (SC20 - SC23) were installed at the same positions as the WLAN APs, operating in FDD mode at a frequency of $2127.6\,\mathrm{MHz}$, using an antenna gain of $2\,\mathrm{dBi}$ and transmitting power of $20\,\mathrm{dBm}$.

B. Calibration and Measurements

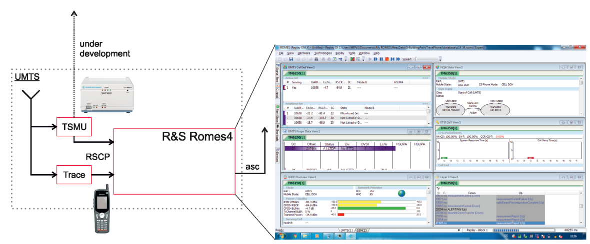
In order to create the radio map, 150 reference points have been selected within the defined area in a grid of $1\,\mathrm{m}$ storing 100 RSS samples at each position for WLAN and UMTS during the offline phase.

As a WLAN client a laptop using a Orinoco Gold Card with an external antenna has been used. In order to create the radiomap and to visualize the position of the WLAN client in real time a software called WIPoS.NET was developed (figure 3).

As a UMTS client a Qualcomm UMTS Test Mobile TM6250 has been used. The RSCP samples were recoreded using the Rohde&Schwarz Romes Drive Test Tool ROMES (figure 3).



(a) WLAN setup



(b) UMTS setup

Fig. 3. WIPoS Tool chain

All measurement data has been exported from ROMES and WIPoS into Matlab for post processing. These tools constitute a powerful tool-chain, which provides an efficient possibility to compare measurements scenarios based on various algorithms. It furthermore provides comfortable visualization outputs such as animation or PDF/CDF of meter error [10].

IV. Results and Discussion

A. WLAN compared to UMTS

Figures 4 and 5 show the CDFs of the accuracies in meter achieved in case of WLAN and UMTS using the following metrics and norms:

- Euclidian distance norm (WLAN$_{Euclid}$,UMTS$_{Euclid}$) based on RSS metric and WKNN algorithm ($k = 4$)
- KL divergence norm (WLAN$_{KL}$,UMTS$_{KL}$) based on RSS metric and WKNN algorithm ($k = 4$)
- Euclidian distance norm based on visibility metric (WLAN$_{Visibility}$,UMTS$_{Visibility}$) with WKNN norm ($k = 4$)

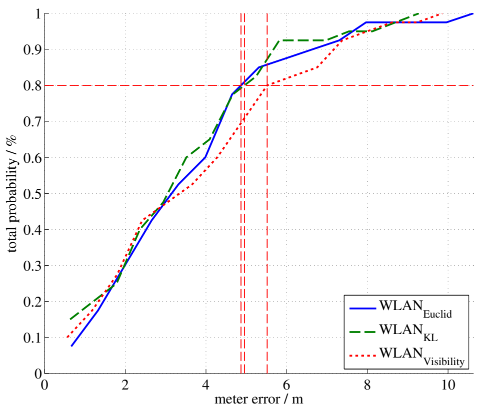


Fig. 4. Accuracies using various metrics & norms for WLAN

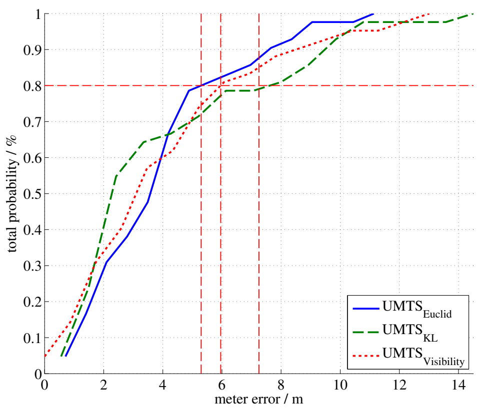


Fig. 5. Accuracies using various metrics & norms for UMTS

As we can see in figure 4, Euclidian distance and KL divergence are outperforming the visibility metric slightly in case of WLAN. Because the visibility threshold needs to be calibrated the RSS based metric is the recommended approach for WLAN localization in order to avoid this additional effort.

The results for UMTS are given in figure 5: At 80% confidence level, Euclidian distance is outperforming KL divergence, on the other hand at 50% confidence levels we achieve better accuracies using KL divergence. Similar results are also achieved when using the visibility metric. Accordingly, in case of UMTS visibility is an alternative metric to RSS based RF-Fingerprinting.

The accuracies achieved in WLAN figure 4 are also similar to the accuracies in case of UMTS figure 5: In both cases a mean localization accuracy of approx. $2\,\mathrm{m}$- $4\,\mathrm{m}$ has been achieved, while at 80% confidence level, the accuracy is slightly better in case of WLAN.

B. Impact of RSS update rate

While for the calibration of the radio map 100 samples have been taken per location within a grid of $1\,\mathrm{m}$ throughout the building, the position estimates during the online phase have been done taking the mean level out of a variable amount of samples.

In our case the WLAN NICs typically update the RSS samples every 2 to 6 seconds in passive scanning mode [8], even though the WLAN beacon is transmitted every 100ms. Pilot level updates in case of UMTS are reported approximately every $100\,\mathrm{ms}$ when the UE is in "connected mode". Considering a pedestrian speed of $0.5\,\mathrm{m/s}$, we have accordingly 20 level updates per meter in case of UMTS, while we only have max. one valid RSS update every meter in case of WLAN, when moving at the same speed.

Table I summarizes the accuracies [m] achieved at 80% confidence level, comparing WLAN versus UMTS in case of a RSS based metric using Euclidian distance and KL divergence as distance norms with a variable amount of samples for position estimation. It can be shown, that almost independent from this amount (1 to 100), a similar accuracy for Euclidian distance and KL Divergence can be achieved in case of WLAN or UMTS.

Accordingly a higher sampling rate had no further impact on the accuracy as long as the measurements are taken under static conditions. The reason for this, is that the RSS fingerprints remain relatively stable per location in case of WLAN and UMTS. In both cases the signal level standard deviation was typically in the range of $2\,\mathrm{dB}$ to $4\,\mathrm{dB}$ (figure6).

In dynamic scenarios, when filter techniques such as Kalman are applied, the higher availability of RSS samples could be beneficial, allowing higher accuracies, especially if the mobile clients are moving at higher speeds. This aspect needs to be further investigated.

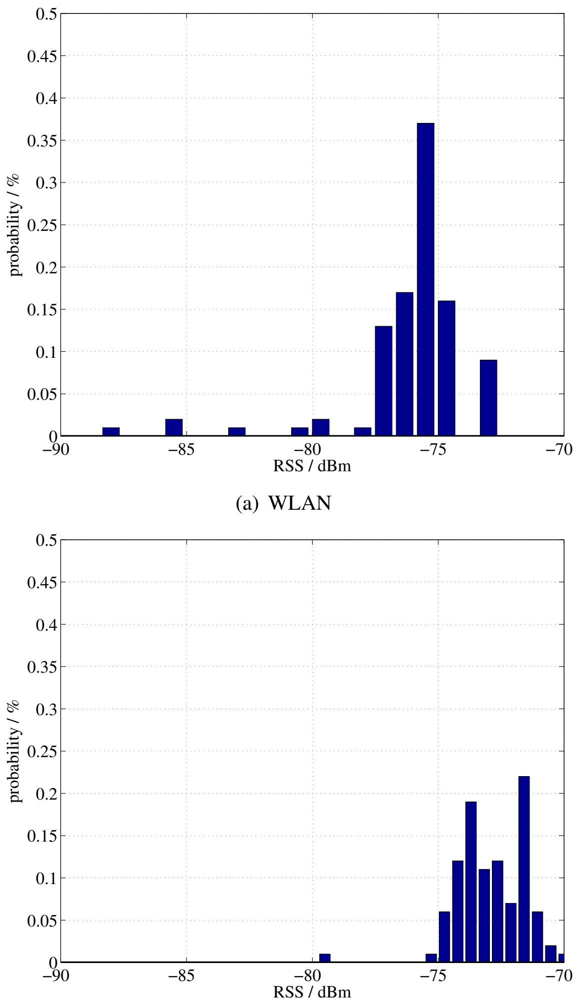
TABLE I
WLAN/UMTS ACCURACIES [METER] AT 80% CONFIDENCE LEVEL WITH KL/EUCLID NORM, RSS METRIC AND VARIABLE AMOUNT OF SAMPLES

#Samples	100	50	20	10	5	1
WLAN KL [m]	4.95	4.4	5.1	4.9	4.48	5.6
UMTS KL [m]	7,25	6.7	7.01	7.04	6.3	6
WLAN Euclid [m]	4.86	4.5	5.12	4.7	4.6	5.18
UMTS Euclid [m]	5.26	5.2	4.66	4.44	4.4	5.79

Comparing the accuracies achieved, when using WLAN and UMTS at 80% confidence level, the conclusions from subsection IV-A are confirmed also in the measurements (table I). In both cases we achieve approx. $5\,\mathrm{m}$ at 80% confidence level, almost independent from the amount of samples, if Euclidean distance is used as a metric. If KL Divergence is used as a distance norm, we can see, that the accuracy in case of WLAN is slightly better ($5\,\mathrm{m}$) than it is in case of UMTS ($7\,\mathrm{m}$) at 80%.

C. Visibility metric and calibrated threshold

Table II summarizes the results by giving the accuracy achieved at 80% confidence level, comparing WLAN versus UMTS in case of visibility metric using various visibility thresholds. A visibility threshold is defined as the min. power level required to consider the measurement of the WLAN Beacon or Pilot RSCP as available (chapter II).



(a) WLAN

(b) UMTS

Fig. 6. PDF of RSS fingerprints of WLAN and UMTS

TABLE II
WLAN/UMTS ACCURACIES [METER] USING WKNN AND VISIBILITY METRIC WITH VARIABLE VISIBILITY THRESHOLDS

Vis. Thres.[dBm]	-85	-80	-75	-65	-60	-55	-50
WLAN [m]	11.8	11.9	9.67	6.3	6.3	5.5	6.2
UMTS [m]	6.19	5.9	13.5	13.9	13.9	-	-

We can conclude from table II, that the visibility threshold needs to be optimized. While we achieve a high visibility granularity in case of UMTS at $-80\,\mathrm{dBm}$ Pilot level, the granularity becomes more significant in case of WLAN at approx. $-55\,\mathrm{dBm}$. In both cases we achieve an accuracy, which is comparable to the accuracies we achieved with RSS based position estimates ($5.5\,\mathrm{m}$-$6\,\mathrm{m}$). Note that other visibility thresholds lead to lower accuracies (table II).

As can be shown in figure 1, the calibrated visibility threshold leads to a location dependent visibility allowing to use the proposed metric according equation 1 for localization purposes.

V. Summary and Conclusion

Based on the results given in the previous chapter it can be concluded, that similar accuracies are achieved with RF-Fingerprinting, when using UMTS Small Cells or WLAN Access Points. In both cases the accuracy is in between $5\,\mathrm{m}$ and $7\,\mathrm{m}$ at 80% confidence level, almost independent from the metric (RSS or visibility), distance norm (Euclidian distance or KL Divergence) or the amount of samples taken during the online phase.

In case of UMTS a valid pilot level is available every $100\,\mathrm{ms}$ (connected mode), while in case of WLAN the RSS value is typically updated only every $2\,\mathrm{s}$ to $6\,\mathrm{s}$ in passive scanning mode. However, under static conditions during the online phase we do not benefit from this higher sampling rate in terms of accuracy. On the other hand the calibration effort is reduced in case of UMTS compared to WLAN, since we can reduce the measurement time during calibration.

If WLAN fingerprinting is applied in public buildings it is recommended to use additional Access Points for localization purposes, which are not using power control or adaptive frequency hopping for interference reduction. In UMTS the same Small Cells can be used for traffic and localization proposes, since the Pilot level is not affected by power control or frequency hopping. This reduces the installation effort and makes RF-Fingerprinting with UMTS Small Cells an interesting alternative.

A visibility metric $Pcov[\%]$ has been proposed as an alternative to RSS based localization (eq. 1). If AP or Pilot visibility is used as a metric, a visibility threshold needs to be calibrated in order to optimize the performance. Since the accuracy is not improved compared to RSS measurements, it is not the recommended approach in order to avoid this additional effort.

It can therefore be concluded, that RF Fingerprinting using UMTS Small Cells is an alternative to WLAN based Fingerprinting, leading to similar accuracies and requiring less installation and calibration effort.

In a future work it is planned to analyze the performance in case of UMTS under dynamic conditions using additional filter techniques. Furthermore it is planed to investigate the accuracies, which can be achieved using a hybrid localization approach, taking advantage from the availability of WLAN and UMTS in todays smartphones.

Acknowledgment

This project was supported by the German Federal Ministry of Education and Research under contract No. 1739B08. We would like to thank our project partners RFS GmbH, Alcatel-Lucent Germany AG and AWE Communications GmbH who always gave us perfect support.

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