Assessment of Cooperative and Heterogeneous Indoor Localization Algorithms with Real Radio Devices


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Abstract—In this paper we present results of real-life localization experiments performed in an unprecedented cooperative and heterogeneous wireless context. The experiments covered measurements of different radio devices packed together on a trolley, emulating a multi-standard Mobile Terminal (MT) along representative trajectories in a crowded office environment. Among all the radio access technologies involved in this campaign (including LTE, WiFi...), the focus is herein put mostly on Impulse Radio - Ultra Wideband (IR-UWB) and ZigBee sub-systems, which are enabled with peer-to-peer ranging capabilities based on Time of Arrival (ToA) estimation and Received Signal Strength (RSS) measurements respectively. Single-link model parameters are preliminarily drawn and discussed. In comparison with existing similar campaigns, new algorithms are also applied to the measurement data, showing the interest of advanced de-centralized message-passing techniques, heterogeneous geometric positioning with hypothesis testing, context-aware localization with e.g., mobility learning or channel-dependent Non Line of Sight (NLoS) mitigation.

I. INTRODUCTION

Designing an efficient indoor localization system requires to determine the good mixture between a wide variety of approaches and algorithms as a function of heterogeneous situations, opportunities and circumstances. How to make it simple, generic and robust? The technical challenge still deserves being addressed by the research community. To tackle the most relevant questions in this context, it is utmost important to rely on real radio data with reliable ground truth meta data. This data collection endeavour has been achieved all along the WHERE2 project [1]. The real-life dataset used in this paper has been intended and designed specifically for jointly heterogeneous and cooperative indoor positioning investigations. It will be made available to the wireless localization community for further studies and algorithmic benchmarking [2].
as well) or on non-cooperative heterogeneous Bayesian navigation [5]. Both attempts rely on IR-UWB devices mostly compatible with the American FCC regulation, with higher bandwidth and higher power consumption.

The remainder of the paper is structured as follows. In Section II, we present the characteristics of the involved ZigBee and IR-UWB radio devices. Section III describes our experimental setup, along with the covered indoor scenarios and preliminary single-link evaluations. Section IV reports positioning results obtained through decentralized cooperative message-passing, geometric algorithm, mobility learning and NLoS compensation based on the measurement data.

II. RADIO ACCESS TECHNOLOGIES AND LOCATION-DEPENDENT METRICS

A. Overall Platform

The WHERE2 measurement campaign has been realized during 4 days in April 2013 in the office building of Portugal Telecom (PTIN) in Aveiro [6]. Different radio access technologies (RAT) have been jointly used to provide a very unique heterogeneous radio database for evaluating positioning techniques, including decentralized and cooperative approaches. During the measurement campaign, all the radio link data associated with each RAT have been stored in a time-stamped database for further offline proost-processing. A measurement testbed has been embedded on a mobile trolley to emulate a multi-standard terminal, which has been moved inside the building. The measurement testbed is equipped with a device of each type of short- or medium-range radio platform and with inertial sensors. Depending on the scenario, data from either all or a selected number of devices have been stored along specific indoor trajectories. Slave radio devices linked to their coordinators on the trolley have been disseminated into the measurement area. Some of those radio devices are mobile whereas most are static access points or fixed anchors with known positions. Figure 1 shows a schematic representation of the WHERE2 testbed embedded on the trolley, along with the additional devices around.

The measurement platform was composed of various devices [6], including ZigBee, IR-UWB, LTE, WiFi and inertial units. In the following we detail the two first radio technologies, since only the corresponding measurements (i.e. representing a subset of the full data amount) are exploited in Section IV as an example of possible database exploitation.

B. ToA-Enabled IR-UWB Devices

The IR-UWB technology, which is generally considered for sensor network deployments, has already proved fine suitability for localization and tracking applications. Over low data rate (LDR) data transmissions at 347 kbps, the devices involved in our measurement campaign allow RTD measurements between peer-to-peer devices [7]. They have been organized in a centralized topology network for measurement convenience, and the coordinator has been placed on the measurement trolley (without loss of generality). At the medium access control level, specific beacon-enabled TDMA ranging transactions are supported with relative clock drift estimation and compensation. As described in [8], these IR-UWB devices operate at the center frequency of 4.5 GHz over a bandwidth of 500 MHz. The modulation scheme is based on Differential Binary Phase Shift Keying (DBPSK) and the receiver enjoys sensitivity of -70 dBm between 4 GHz and 4.5 GHz. Among other physical metrics these nodes provide ranging timers associated with Time of Arrival (ToA) estimates within the time resolution of 1 ns, which can be directly converted into a RTD, and hence into a relative distance. They provide also estimated channel energy profiles at the same resolution for further analysis.

C. RSSI-Enabled ZigBee Devices

The involved ZigBee nodes are IEEE 802.15.4 compliant RF transceivers based on the CC2431 chip from Texas Instruments, which were designed for generic ZigBee low-power and low-voltage wireless applications. These devices operate in the ISM band, at the center frequency of 2.4 GHz over a 5 MHz bandwidth [8]. The modulation is based on DSSS / OQPSK and the theoretical receiver sensitivity is around -92 dBm. RSS measurements can be issued over standard peer-to-peer communication links. Similarly to IR-UWB, the used ZigBee devices are organized in a centralized cooperative topology network, which means that a device has to be configured as a coordinator. Here, this coordinator node has been placed on the measurement trolley for convenience.

III. EXPERIMENTAL SETUP: COOPERATIVE AND HETEROGENEOUS SCENARIOS

A. Measurement Scenarios

The overall WHERE2 measurement campaign is rich and made of 4 different scenarios, each including several sub-scenarios. Each one takes into account a large number of situations involving mobile nodes, different RATs, and different visibility situations. In the following only 2 specific scenarios have been selected and discussed.
1) Scenario A: This scenario (Referenced as Scenario 2 in [6]) gathers data from all the RATs where all the nodes are static except the moving trolley. It is mostly intended here for extracting single-link ranging and path loss model parameters for the two selected technologies. The trolley with both ZigBee and IR-UWB coordinating nodes has been moved on 18 different measurement points in the building, as shown on Figure 2a. In addition, 15 IR-UWB and 7 ZigBee devices have been disseminated around, providing measurements between each other and with respect to the trolley.

2) Scenario B: This scenario (Referenced as Scenario 4 in [6]) gathers data on a finer ground truth point grid (i.e. 1 point every 0.5m), making it possible to emulate a continuous trajectory. All the devices (including blind targets) except those embedded on the trolley are still static, standing at the same positions as previously, as shown on Figure 2b.

B. Single-link Models

Before feeding localization algorithms with the collected measurements (See Section IV), single-link parameters are extracted from Scenario A first.

1) ZigBee RSS Path Loss & Shadowing Models: Figures 3a and 3b represent a selected example (link 48-18) of the received power and the associated ground truth distances as a function of the tested trolley position. For a specific occupied point, numerous consecutive power measurements have been performed. The red dots represent the mean values of these measurements. It is thus observed that the received power is rather weakly correlated with the distance. As expected in case of strong received power the relation to distance is clearer. It also appears that there is a quite significant number of radio links which return the saturated minimal value of $-81 dBm$, which corresponds to the practical sensitivity of the receiver. In the following, radio links exhibiting such RSS values, which are less informative with respect to the true distance, have been ignored when determining the path loss parameters.

Denoting by $RSS$ the RSS value in dB at the true distance $d$, $RSS_0$ the reference RSS at $d_0 = 1 m$, $n_p$ the path loss exponent, and assuming $X_\sigma$ as a zero-mean Gaussian random variable representing the shadowing, it can be written:

$$RSS = RSS_0 - 10n_p \log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \quad (1)$$

Applying a linear regression (in the Least Squares sense) onto the measured data, the overall (multi-link) and node-specific parameters associated with the previous standard log-normal shadowing model have been extracted, as reported in Table I and illustrated in Figure 4.

Table I: ZigBee RSS path loss models extracted from Scenario A

<table>
<thead>
<tr>
<th>ZigBee NodeID</th>
<th>$RSS_0$ (dBm)</th>
<th>$n_p$</th>
<th>$\sigma$ (dBm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>-50.21</td>
<td>2.21</td>
<td>5.73</td>
</tr>
<tr>
<td>30</td>
<td>-51.38</td>
<td>1.16</td>
<td>6.85</td>
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<tr>
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<td>-55.45</td>
<td>2.01</td>
<td>3.20</td>
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<td>39</td>
<td>-47.14</td>
<td>2.48</td>
<td>5.93</td>
</tr>
<tr>
<td>46</td>
<td>-47.33</td>
<td>3.07</td>
<td>4.56</td>
</tr>
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<td>48</td>
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<td>4.98</td>
</tr>
<tr>
<td>49</td>
<td>-52.77</td>
<td>2.68</td>
<td>4.56</td>
</tr>
</tbody>
</table>

Fig. 4: Received power as a function of the true distance of each ZigBee device. The black line, red line and blue line represent the LS-fitted single-slope path loss model for all the nodes, node 30 and node 49 respectively.

Out of the extracted values, it is clear that the received power suffers from very large variability. This harmful dispersion is also observable over static links. As an example, the received power measured as a function of time over 2 static
The robust geometric positioning algorithm (RGPA) in introduced in [9] is a low-complexity procedure incorporating any kind of location dependent parameter (LDP), including radio metrics or prior map knowledge, in the form of geometric constraints. Accordingly it is intrinsically suitable to heterogeneous localization contexts. Final location estimates are thus computed based on the intersection of bounding geographic areas. RGPA has been applied here on the measurement data and further compared to a heterogeneous ML algorithm initialized with a random guess as described in [10]. In the particular case of complete hybridization (including both ZigBee and IR-UWB LDPs), and only 2 IR-UWB are available, the position estimation has been performed using RGPA coupled to an hypothesis testing method presented in [11]. This approach, denoted RGPA HT, uses RSS information to contextually solve out geometric ambiguities (multi-modal solutions) which can occur in those cases of low IR-UWB connectivity conditions. In the following, we consider the single-link models extracted in Subsection III-B as a priori information whereas the dataset of Scenario B is used for performance evaluation with ZigBee RSS measurements only, IR-UWB ToA-based range measurements only, or both kinds of metrics. The number of available observables depends on the trolley’s position and thus, on local connectivity conditions.

Figure 6 represents the CDFs of positioning error for both RGPA and ML using only ToA-based range measurements. It can be observed that RGPA outperforms the ML in the regime of low errors. Thus, 90% of the positions are estimated with an error inferior to 3 meters using RGPA whereas the ML achieves an error lower than 4 meters in a similar situation. However, for a few occupied positions with larger estimation errors, the ML still prevails on the RGPA. On the contrary, comparing the CDFs of positioning errors using only RSS observables, the ML outperforms the RGPA approach. This result can be partly explained by both the difficulties of RGPA to bound properly a RSS constraint as explained in [9] and by the large variability of RSS measurements. That trend is confirmed in heterogeneous cases where RSSs are used in addition to ToAs, where no improvement can be observed compared to the only use of TOAs. The RGPA HT globally outperforms the ML algorithm in the regime of small errors (under 3 meters), and is slightly less accurate than the ML from this distance. However, RGPA HT reduce significantly the computational complexity in comparison with ML, using only RSS information to take a decision in case of multi-modal ambiguity due to the TOA position estimation.
B. Cooperative Message-passing in Loopy Networks

Standard approaches based on message-passing procedures for cooperative localization named NGBP (Non Gaussian Belief Propagation) and based on junction trees (NGBP-JT) are only tractable for small-scale networks because of the high complexity of the junction tree formation and the high dimensionality of the particles. Therefore, we propose NGBP based on a pseudo-junction tree (NGBP-PJT), which represents an approximated junction tree based on thin graph. PJT is created assuming that i) the number of cliques is limited (e.g., in the order of the number of nodes), ii) each clique includes no more than 3 nodes to decrease the problem dimensionality and iii) one can avoid expensive triangulation. In order to satisfy the first two conditions, we need to decrease the number of edges in the graph by forming a thinner graph. That can be easily done using a modified version of the breadth first search (BFS) method. This modification will make a graph with a small number of short loops, but not a spanning tree. Then these short loops can be used to make 3-node cliques, and the rest of the pairs form 2-node cliques. Having defined cliques, we can form the cluster graph by connecting all pairs of cliques with a non-empty intersection. However in order to decrease the number of high-dimensional particles, we use more informative importance density function, and also propose dimensionality reduction of the messages [12], [13].

For the previous methods, we need to make some kind of graph transformations before applying the message passing method. This can be avoided using tree-reweighted NBP (TRW-NBP). However, finding edge appearance probabilities for each edge is intractable (especially, for distributed implementations) except for certain types of graphs. Therefore, we consider the case with uniform “edge appearance probabilities”, characterized just by a scalar variable. For the novel uniformly-reweighted NBP (URW-NBP) method, we obtained empirical values of that scalar variable as a function of the node degree in the network. Through Monte Carlo simulations, we have verified performance gains in terms of Root Mean Square Error (RMSE) and Kullback-Leibler Divergence (KLD) with respect to the true distribution, as already described in e.g., [14].

This last option is the one implemented and applied onto real measurements in this paper. The CDF of positioning error with IR-UWB input measurements in Scenario B is shown for illustration in Figure 7. The best performance is thus obtained when assuming in the algorithm the prior ranging error model with the highest error variance, while using the linear distance approximation over mobile-to-fixed links presented in Eq. (2). The positioning error in this case is for instance below 2 meters in 80% of the trolley positions.

C. Hidden Markov Model Based Mobility Learning

This contribution uses the Hidden Markov model (HMM) based algorithm presented in [15] to improve the estimated users’ trajectories. This algorithm does not work iteratively, so online tracking is not computationally efficient. It is more useful for the offline smoothing of observed trajectories. It can take as inputs some location estimates from any side localization algorithm. In this paper, we have used measurements from Scenario B and the RGPA algorithm described in Subsection [V-A]. In essence, the applied HMM based algorithm combines mobility model constraints (like in tracking Kalman Filters) with a mapping between observations and true locations (like in a fingerprinting based localization system).

Similarly to the previous work in [15], we assume that the considered scenario is discretized into grid cells of $1 \times 1$ m$^2$. A user movement trajectory thus consists of a time-sequence of visited grid cells. Location estimation errors will in many cases cause the observed grid cell to be different from the grid cell where the user is actually located at that time. The algorithm primarily relies on the following three main components: i) the transition probability matrix $P$, in which equal transition probabilities have been inserted between neighboring points in Fig. 2b; ii) the observation probability matrix $B$ that for each possible true grid cell specifies the likelihood of the observations; and iii) the Viterbi algorithm which uses these
two matrices along with initial state probabilities to determine the most likely sequence of true grid cells (i.e. a best guess of the users actual trajectory) given a sequence of observations (position estimates) from the localization system.

In this paper the measurement data has been used to populate the observation probability matrix $B$, so that for each true grid cell, $B$ contains a Gaussian probability distribution with standard deviation of 1 meter around the corresponding observed grid cell. Here the $B$ matrix allows us to account for measurement bias due to propagation effects. Notice that this differs from the work in [15], where only a zero mean Gaussian probability distribution around the true grid cell was used. The results in Fig. 8 shows the CDF of the achieved positioning error, in comparison with that of feeding location estimates (i.e. initially issued by RGPA). For these evaluations, we have considered four individual test trajectories each covering parts of the entire trolley’s trajectory in Fig. 2b. The HMM based algorithm is thus able to reduce the positioning error from 7.5 m at 90% down to 3 m for the RSS measurements, whereas the improvement is from 3 m down to 1 m at 90% when using both RSS and ToA kinds of measurements. These are rather convincing results. However in cases where the mobility model is not known so well in advance and where it is possible to use different stochastic realizations of measurements from each grid cell for training and testing, the gains are expected to be less significant.

D. NLoS Ranging Bias Mitigation Based on Channel Impulse Responses

Multipath phenomena, blockages of the direct path or transmissions through the walls and pieces of furniture notoriously result in excess delays and make ToA-based ranging measurements positively biased. In this section, we exploit estimated channel impulse responses (CIR) within the resolution of 1 ns over IR-UWB links [2] for mitigating NLoS ranging bias and improving localization accuracy. We distinguish between three link states: State $H_0$ or line of sight (LoS) when the direct path is unobstructed, state $H_1$ when the direct path is obstructed by walls or NLoS, and state $H_2$ when the direct path is obstructed by metallic furniture or deep NLoS. The ranging measurements are assumed to be corrupted by additive errors. For Scenario B, as shown in Table II the values of the mean and standard deviation of the ranging error are found to be, respectively, 0.4 m and 0.5 m under $H_0$, 1.5 m and 0.8 m under $H_1$, and 2.2 m and 1.1 m under $H_2$. Thus the knowledge of the link state enables using the appropriate bias value or probability distribution of the ranging error by the localization solution.

The following metrics extracted from the CIR are used for classifying the links: The root mean squared delay spread ($\tau_{rms}$), the kurtosis and the maximum CIR amplitude. These metrics are computed for the links of Scenario B, and the corresponding CDFs under the three states are shown in Figure 9. These three metrics were used for characterizing the LoS and NLoS conditions in [16, 4], where measurement campaigns revealed that in LoS situations the kurtosis and the maximum amplitude are more likely to take higher values while the delay spread is more likely to take smaller values. This is consistent with the results shown in Figure 9 except for $\tau_{rms}$ under $H_2$ and the kurtosis under $H_0$. This might be due to the fact that the environments of the measurement campaigns differ in the layout, the kind of obstructions and the placement of the nodes. For example, in [4] the nodes are placed in the middle of the rooms, while in Scenario B most of the static nodes are either placed near the corners or stuck to the walls for the sake of respecting realistic deployment constraints. The estimated probability distributions of the CIR metrics under the three link state conditions are fitted to mixtures of Gaussian functions. The maximum likelihood (ML) estimator is applied for classifying the links of Scenario B by assuming that the metrics are independent. The ratios of correct classification are about 0.7 under $H_0$, 0.7 under $H_1$ and 0.9 under $H_2$.

The localization accuracy is studied by considering a configuration derived from Scenario B where 9 static nodes are selected as anchors and 4 static nodes are selected as blind targets to be positioned. The selection of the anchor nodes is made in a way that guarantees both a coverage of a big portion of the network deployment area and a good GDoP. We select 70 test positions at which the trolley node is connected to at least three nodes among which there is at least one target node. In this configuration, only 16 of the
trolley positions enjoys connectivity to three or more anchor nodes. Thus, cooperation is definitely needed for guaranteeing unique location solutions in most of the target positions. The applied localization algorithms are the distributed two-phased nonparametric belief propagation (TP-NBP) adapted from [17] and the centralized weighted least-squares (WLS) [18]. In a distributed implementation, the cooperating nodes need to know the statistical parameters of the distribution function of the ranging error under the different link states and the classification rule or the distribution functions of the CIR metrics. Figure 10 plots the CDFs of the positioning error with and without prior link classification. It shows that classification improves localization accuracy, as expected. The facts that most of the links of the tested configuration are in LoS and that the accuracy without classification is already good enough make this improvement modest. Figure 10 also shows that the centralized WLS is slightly more accurate than the distributed TP-NBP in the same scenario, but generating extra traffic and latency to collect all the cooperative measurements.

V. CONCLUSION

This paper has presented a real-life dataset designed specifically for heterogeneous cooperative indoor positioning investigations and provided comparisons between different algorithmic approaches performances. The dataset is available for download to share the measured results of the different devices. The dataset was analyzed to describe the 1st (mean) and 2nd (variance) order statistics. Several types of algorithms were evaluated by the dataset. Depending on the algorithm the performances in terms of RMSE ranges below 1m and less than 7m for 80% of the cases in such challenging environment with numerous reflections, changing line-of-sight to non-line-of-sight conditions and vice versa.

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