Cooperative and Heterogeneous Indoor Localization Experiments

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Abstract—**In this paper we present the results of real-life localization experiments performed in an unprecedented cooperative and heterogeneous wireless context. These measurements are based on ZigBee and orthogonal frequency division multiplexing (OFDM) devices, respectively endowed with received signal strength indicator (RSSI) and round trip delay (RTD) estimation capabilities. More particularly we emulate a multi-standard terminal, moving in a typical indoor environment, while communicating with fixed OFDM-based femto-base stations (Femto-BSs) and with other mobiles or fixed anchor nodes (through peer-to-peer links) forming a wireless sensor network (WSN). We introduce the measurement functionalities and metrics, the scenario and set-up, providing realistic connectivity and obstruction conditions. Out of the experimental data, preliminary positioning results based on cooperative and geometric algorithms are finally discussed, showing benefits through mobile-to-mobile cooperation, selective hybrid data fusion and detection of unreliable nodes.**

I. INTRODUCTION

Most of our usual environments comprise heterogeneous wireless resources, such as WiFi access points (APs), Long Term Evolution (LTE) femto base stations (Femto-BSs) and wireless sensor networks (WSNs). These environments are also densely crowded by multi-standard mobile terminals (MTs) cooperating directly over short or medium ranges. In such environments, the radiolocation capability has been identified as a key feature to enhance the connectivity experience (e.g. through vertical handover) and to enable indoor navigation or context-based services [1].

Algorithmic works reported in the recent literature have been focusing on decentralized iterative positioning (e.g. [2], [3], [4]) on the one hand, and cooperative links selection (e.g. [5], [6]) on the other hand, but the localization performance has been most often assessed through simulations so far. The latter evaluations cannot account for complex phenomena inherent to cooperative and heterogeneous contexts, such as space-time correlations between the different involved radio access technologies (RATs), the conjunction of harmful sparse connectivity and poor geometric dilution of precision (GDoP) conditions, or erratic radio obstructions experienced along the MT trajectory (e.g. [7]). Finally, experimental investigations have been carried out more recently, though dealing uniquely with cooperation in homogeneous scenarios (e.g. [8]).

In this paper, we describe a localization-oriented measurement campaign realized in a jointly cooperative and heterogeneous wireless indoor context. ZigBee devices are enabled with received signal strength indicator (RSSI) measurement capabilities whereas an OFDM setup allows for round trip delay (RTD) estimation, making possible the emulation of a multi-standard MT. Applying decentralized iterative message-passing and non-cooperative geometric positioning to the extracted experimental data, we show benefits through selective peer-to-peer (P2P) short-range cooperation and multi-RAT hybrid data fusion, considering different path loss and ranging error models to represent such harsh indoor scenarios.

The paper is structured as follows. In Section II, we recall the characteristics of the involved Zigbee and OFDM radio devices. Section III describes our experimental setup, along with the covered indoor scenarios. Section IV subsequently reports positioning results obtained through decentralized cooperative message-passing and geometric algorithms based on the measurement data.

II. AVAILABLE RADIO ACCESS TECHNOLOGIES AND LOCATION-DEPENDENT METRICS

A. RTD-Enabled OFDM Devices

In the context of the WHERE2 project [1], we developed a flexible test-bed that allows for P2P ranging based on analogue amplify RTD. Fig. 1 shows the test-bed [9] embedded in the multi-standard MT. The analogue amplify RTD determines, based on the fixed processing delay in the return node, the distance similarly to the time of arrival (ToA) method. The test-bed consists of two parts, a master node and a slave node. The master node transmits an OFDM modulated signal to the slave node. The slave node returns this signal amplified. The master node receives the signal from the slave node and estimates the RTD to determine the distance. This approach simplifies the synchronization between both nodes. The key

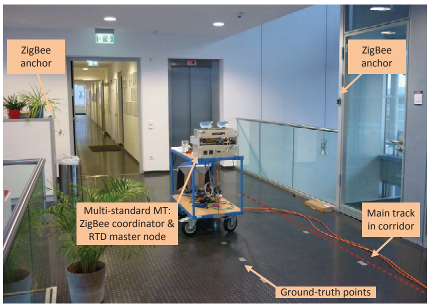

Fig. 1. Multi-standard MT mounted on a trolley in the small open area.

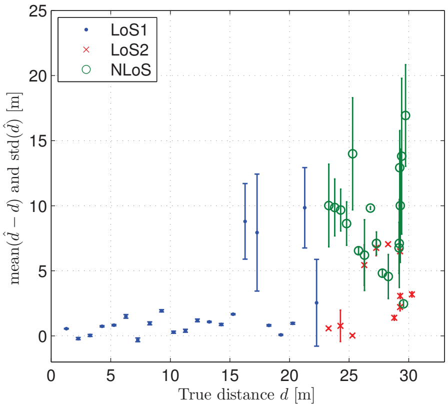

Fig. 2. RTD ranging performance versus distance with a correlator in the investigated indoor environment: LoS1 (in the long corridor), LoS2 (after the corridor in the open space), and NLoS (in the open space).

system parameters are a sampling rate of 120 MHz with a subcarrier spacing of 14.65 kHz. Only the inner 512 subcarriers are active, resulting in an effective bandwidth of 36.62 MHz. The center frequency of the master-to-slave link is 5.5 GHz and the reverse link is 5.7 GHz. The transmit power was limited to 21 dBm.

RTD estimation is based on a correlation receiver with interpolation. Thus, it is possible to obtain fractional sample delays, which lead to higher ranging accuracy. The structure of the OFDM modulated signals is similar to that used in 3GPP-LTE. This allows for future investigations of flexible allocation schemes of subcarriers to steer the ranging performance depending on the requirements. Fig. 2 shows the ranging performance versus distance for different propagation conditions in the investigated indoor environment. We distinguish between three constellations characterized by the position of the MT: corridor (LoS1), open area close to the right end of the corridor (LoS2), and open area (NLoS), see the dotted-line trajectory on Fig. 4. The two former constellations correspond to line of sight (LoS) transmissions, whereas the latter is for non-line of sight (NLoS) conditions. As expected we can observe in Fig. 2 a performance degradation as the distance between the RTD anchor and the MT increases. The larger errors observed at the end of the corridor and in the open area are caused by more severe multipath propagation.

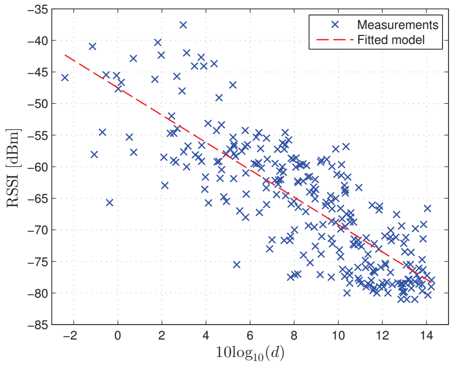

Fig. 3. Cluster plot of the experimental RSSI values in Setup 1 (see III-A) versus distance, with the path loss model using the "global" settings.

B. RSSI-Enabled ZigBee Devices

Other radio transceivers developed in WHERE2 and involved in the measurement campaign are based on the CC2431 chip from Texas Instruments [10], which is suitable for IEEE 802.15.4 and ZigBee applications. Regarding RSSI measurements, the most relevant CC2431 radio parameters are the operation frequency of 2.4 GHz with a bandwidth of 5 MHz, a TX power of 0 dBm and a RX sensitivity of -92 dBm.

To infer on the ranges from experimental RSSI readings we use the one-slope path loss model [11], whose parameters are the reference power P_0 at the distance $d_0 = 1$ m, and the path loss exponent n_p, which characterizes the power decay versus distance. The deviations of experimental RSSI values from the path loss model are commonly modeled as realizations of a zero-mean Gaussian r.v. with variance σ_{sh}^2.

These path loss parameters are environment dependent and as such must be determined empirically from a set of calibration measurements. For the results presented hereafter we considered using the measurement setup described in Section III-A and Least Squares (LS) data fitting. The parameters extracted for this site-specific "global" model (vs. respectively the "data sheet" parameters provided by the manufacturer in an unspecified scenario [10]) are P_0 = -47 dBm (resp. -42 dBm), $n_p = 2$ (resp. 3) and $\sigma_{sh} = 5.8$ dB (resp. 5 dB).

III. Measurement Setups and Scenarios

In the WHERE2 project, several measurement campaigns (including the experiments described herein) are scheduled for algorithm validations and benchmarking by interested partners. The corresponding data is available on the project website [1].

A. Setup 1: Cooperative and Heterogeneous Scenario

In this setup we aim at covering the whole measurement area with the used ZigBee nodes. This allows the verification of various algorithms enabling e.g., (non-)cooperative positioning or the extraction of shadowing maps. Fig. 4 shows a simplified floor plan with the positions of the ZigBee nodes and the RTD slave anchor and Fig. 1 depicts a photograph of the measurement setup. The RTD slave node is located at the end of the corridor, to allow LoS ranging for the majority

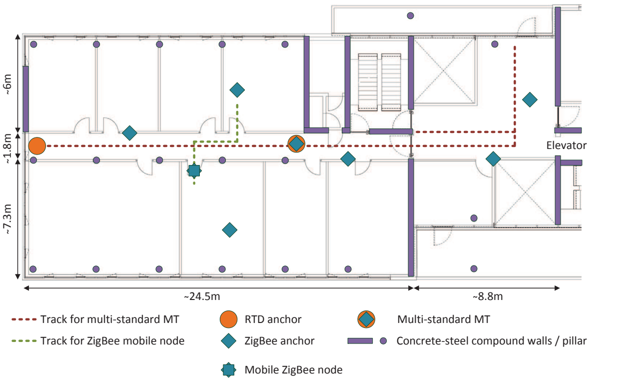

Fig. 4. Cooperative and heterogeneous Setup 1: Back-and-forth trajectory of a multi-standard OFDM-RTD/ZigBee MT in a corridor and small open area with 7 ZigBee anchors and 1 RTD anchor.

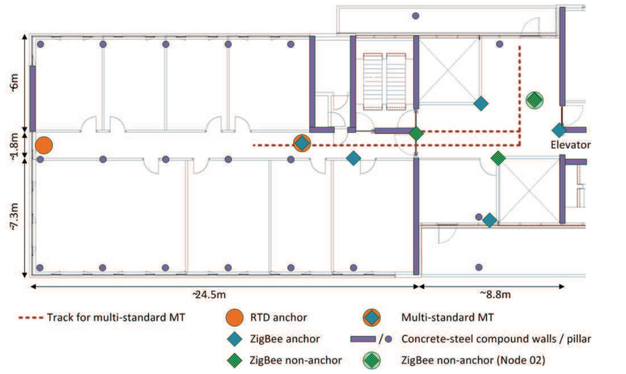

Fig. 5. Cooperative and heterogeneous Setup 2: Identical multi-standard MT track but with locally higher short-range peer-to-peer connectivity in the small open area.

of ground-truth points (GTPs). The ZigBee anchors are distributed in a way to satisfy the limited communication range as well as to reduce the GDoP along the main track. Our multi-standard MT is composed of the RTD master node and one ZigBee coordinator mounted on a trolley. Measurements are performed at stationary positions for approximately 100 s each. GTPs along the corridor are separated by 1 m whereas GTPs perpendicular or parallel to the corridor track are separated by 0.5 m, with an accuracy better than 2 cm. Furthermore, we chose one ZigBee node mounted on a tripod as mobile node, crossing the main track in the corridor, see the green dashed line in Fig. 4. The multi-standard MT moves from the RTD slave node along the corridor, whilst in parallel, this specific mobile node walks along its own GTP-track. This additional node could be exploited either as moving anchor node or as cooperative node with estimated position.

B. *Setup 2: Impact of Peer-to-Peer Connectivity*

The second measurement setup aims at a further evaluation of P2P cooperation. All ZigBee nodes are located in a small open space area, see Fig. 5. Thus, multiple P2P links are available and the positioning system is hopefully overdetermined. This helps to evaluate the potential of more sophisticated cooperative positioning algorithms, GDoP reduction and link selection. The measurement procedure is similar to that used for Setup 1, but we start in the middle of the corridor. This ensures a fully connected network in which the ZigBee coordinator on the MT has valid ranging links to all anchors.

IV. Tested Algorithms and Results

In this section, we apply selected positioning algorithms developed in WHERE2 [12] onto experimental ranges derived from RTD and RSSI measurements (from both Setups 1 and 2). RSSI-based range information is derived using estimators from [13], while using the path loss model parameters discussed in Section II-B.

A. *Non-Cooperative Positioning*

The non-cooperative RGPA algorithm described in [14], which is based on a geometric representation of location dependent metrics (LDPs), is applied to experimental data from measurement Setup 1. We consider all the RSSI values measured between the fixed ZigBee anchors and the ZigBee coordinator of the multi-standard MT. Fig. 6 shows the cumulative distribution function (CDF) of estimated location errors, with and without incorporating the RTD measurement on top of the RSSI measurements, illustrating the benefits that can be achieved through hybrid data fusion in comparison with homogeneous localization. This is due to the fact that in Setup 1 LoS conditions prevail and that generally the distances are large, and as such RSSI-based ranging errors are large, which leads to a significant improvement from the RTD measurements. Fig. 6 also presents a comparison with a randomly initialized non-cooperative maximum likelihood (ML) algorithm. The comparison reveals that the geometric algorithm slightly outperforms the ML solution in the small and medium location error regimes, while suffering from performance degradation in the order of 1 m only in the worst case location error regime caused by severe measurement outliers (i.e. beyond a location error of 4 m at 90% of the CDF). In this region, the ML error would be anyway larger than practical target thresholds in most indoor applications. Furthermore, in comparison with ML, RGPA is completely non-parametric and less demanding in terms of computational complexity as heterogeneous constraints are incorporated. As an illustration, the relative processing time elapsed during our simulations after incorporating the RTD is slightly increased by a few percents for RGPA but doubled for ML in comparison with the homogeneous case. Moreover, the ML processing time could be larger than that of RGPA by 15 to 20% in a similar heterogeneous case.

B. *Cooperative Positioning*

We now compare two cooperative decentralized positioning solutions, namely the variational message-passing (VMP) algorithm [2] and a two phased - nonparametric belief propagation algorithm adapted from [4], with a cooperative centralized weighted least squares (WLS) algorithm [15] initialized through semi definite programming (SDP) [16] and with a non-cooperative decentralized anchor centroid (AC) solution

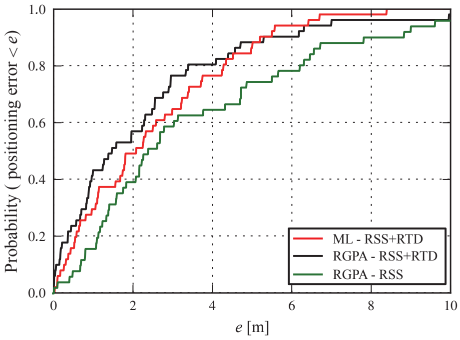

Fig. 6. CDF of positioning errors for the RGPA and randomly initialized ML positioning algorithms in Setup 1, with and without including the RTD measurement on top of RSSI measurements.

[17]. The latter is used for initialization in the VMP algorithm. VMP uses link-specific standard deviations in the distance-error model. These standard deviations are computed from distances estimated from multiple RSSI readings. For the RTD measurement we distinguish between LoS and NLoS conditions and set the standard deviation to 0.25 m and 1.5 m, respectively. As for TP-NBP, we consider incorporating RTD only for LoS links, assuming centered Gaussian errors, or in both LoS and NLoS cases, but assuming that the measurements follow a bi-modal mixture of Gaussian distributions. For the WLS algorithm we select the weights as $w_{i,j} = 1/\hat{d}_{i,j}^2$ where $\hat{d}_{i,j}$ is the estimated distance between nodes i and j. The AC algorithm solely relies on the positions of anchors to which a link is available. For all these algorithms we consider the data from the fixed OFDM RTD anchor, 4 fixed ZigBee anchors, 3 ZigBee non-anchor nodes (with unknown positions) and the multi-standard mobile trolley in Setup 2 (see Fig. 5). We estimate the positions of the non-anchor nodes and the mobile trolley. Fig. 7 shows the CDFs of the corresponding positioning errors.

In the homogeneous cooperative case (see top curves of Fig. 7), we observe that all algorithms perform better than the AC method. For position errors larger than 4 m all algorithms are above 75% of the CDF, where WLS and TP-NBP perform better than (and VMP performs similar to) the AC method. We also notice that VMP and WLS seem to perform equally well for practical error ranges smaller than 3 m, while slightly outperforming the TP-NBP solution.

Regarding node 02 (see Fig. 5), we could observe rather frequent disconnections of its links and systematically over-estimated distances for at least one of the available links. Focusing on the VMP performance (see middle curves of Fig. 7) we thus remark that positioning errors initially larger than 2 m can be improved after discarding this unreliable node and its RSSI readings. More specifically an error gain of about 1 m is obtained at 80% of the CDF. This example illustrates the benefits of identifying and incorporating solely the most reliable cooperative nodes. This problem is one of the ongoing topics in WHERE2 (e.g. based on link quality, GDoP, theoretical bounds, or combined criteria [5], [6]).

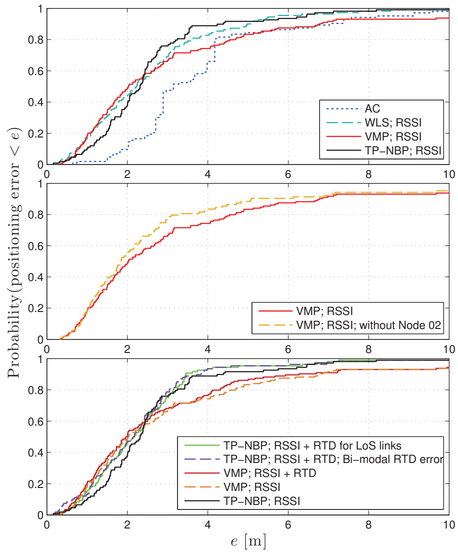

Fig. 7. CDF of positioning errors for the nominal AC, VMP, TP-NBP and WLS algorithms in Setup 2 (top). VMP is shown excluding unreliable "Node 02" (middle) whereas both VMP and TP-NBP are shown including the RTD measurement on top of RSSI measurements (bottom).

Including RTD measurements (see bottom curves of Fig. 7), we observe only a small benefit for position errors larger than 3.8 m in the VMP algorithm, whereas quite significant gains are observed with TP-NBP while performing selective hybrid data fusion, that is, after incorporating only LoS measurements under the standard Gaussian error assumption or both NLoS and LoS measurements under a global bi-modal error assumption. Advantageously the latter approach does not necessitate any prior NLoS detection step. One may also expect that applying high-resolution techniques for single-link RTD measurements should provide much better robustness against multipath, and thus significantly lower RTD variance. Therefore, fusion results using LoS measurement data could be even more stable whereas systematic biases could be more easily mitigated in identified NLoS areas.

In addition to accuracy, the latency and communication cost of cooperative algorithms may be critical under real-time constraints. These factors depend on the number of iterations and on the computational complexity per iteration. In the family of NBP-based algorithms for instance, the order of complexity at one node is $O(d.M^2)$ where d is the number of 1-hop neighbors and M is the number of particles. However the number of needed iterations is generally smaller than the network graph diameter. In dynamic cooperative localization, after initialization, one iteration can be sufficient, and drawing the particles from a motion model can reduce even further the computational complexity.

C. Sensitivity to a priori Path Loss Models and Parameters

We finally investigate the sensitivity of the RGPA and VMP positioning errors to different path loss model settings in the prior RSSI-based ranging step. The CDFs of position errors are shown for each algorithm using two different path loss model

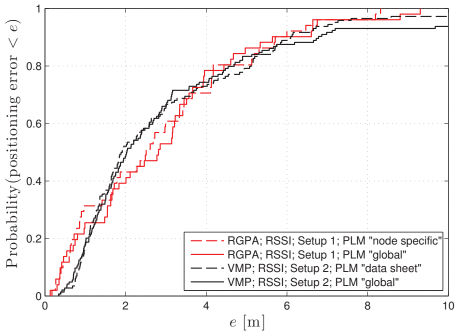

Fig. 8. CDF of positioning errors for RGPA and VMP using the different path loss model settings reported in Section II-B.

settings in Fig. 8. The results for VMP are obtained for Setup 2 using the "global" and "data sheet" settings. The results for RGPA are obtained for Setup 1 using the "global" path loss model, and using an individual setting for each ZigBee node termed "node specific" in the figure. The set of such "node specific" models provides only a slight improvement over the "global" path loss model in the practical error range for indoor localization (i.e. up to 3 m). Hence from these preliminary results no clear benefit from using individually tailored settings is seen. The CDF of VMP shows that the algorithm is even rather insensitive to the selected path loss model. This apparent insensitivity is likely caused by the relatively large and prevalent variance of the RSSI measurements. The same effect could also explain why the RGPA results do not improve much when "node specific" models are utilized, even though the self-learning of node/environment specific parameters has already been shown valuable [7].

V. Conclusion

In this paper we presented a heterogeneous and cooperative positioning test-bed. This test-bed combines a single OFDM-based radio device using time-based distance measurements together with multiple ZigBee nodes relying on the received signal strength indicator. The measured data was post-processed by different positioning algorithms, including a variational message-passing approach, a two phased - nonparametric belief propagation solution and a robust geometric algorithm, all developed in the frame of the WHERE2 project. Cooperative positioning in indoor environments must classically cope with fast changing conditions, in terms of individual nodes mobility and problem geometry. In our investigations, the involved ranging devices also created additional measurement outliers (e.g. one node being even unreliable), which are representative of real-life operating conditions. This causes new challenges for the algorithms that were investigated and compared. A few insights have thus been disclosed in favor of context-aware data fusion (e.g. depending on LoS/NLoS condition) and selective cooperation through links weighting or nodes censoring. Furthermore, even if most algorithms are parametric and require a priori models for the measurement data, they seem to be rather insensitive to using either values from the literature or refined models based on in-site measurements, at least in practical indoor localization error regimes.

New experiments scheduled in WHERE2 will involve low data rate Ultra Wideband (UWB) devices as additional heterogeneous resources. The latter will contribute to increase short-range peer-to-peer connectivity, while providing high ranging precision. On this occasion, complementary algorithmic aspects shall be addressed, such as convergence issues or real-time processing constraints within message-passing algorithms, as well as links selection mechanisms.

Acknowledgment

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