UWB/Wi-Fi RTT Integration for Personal Mobility Applications of CP User Groups*

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Abstract

Modern mobile devices offer advanced capabilities for navigation and Location-Based Services (LBS). This study investigates the use of Ultra-Wideband (UWB) and Wi-Fi Round-Trip Time (RTT) measurements for pedestrian localization across various scenarios. We analyze the ranging accuracy of these techniques and evaluate positioning performance using different fusion algorithms. Our proposed collaborative positioning (CP) methodology enhances localization accuracy for user groups within a defined area. Results demonstrate significant improvements in position trueness, with UWB and Wi-Fi RTT achieving enhancements of 74% and 54%, respectively. Additionally, our localization algorithm, leveraging a Peer-to-Infrastructure (P2I) and Peer-to-Peer (P2P) hybrid configuration, increases anchor availability by up to 10%. Even in short-duration anchor loss scenarios (P2P-only), position trueness improves by up to 53%. These findings highlight the potential of UWB and Wi-Fi RTT in real-world pedestrian localization, particularly for urban navigation, smart mobility applications, and emergency response systems.

1. Introduction and Motivation

Tracking vehicles, pedestrians, and assets in different environments is crucial for various societal applications nowadays due the increasing use of "smart" devices (Papathanasopoulou et al., 2024). These devices can provide high-quality positioning services which have become essential, especially for wirelessly connected devices. While Global Navigation Satellite Systems (GNSS) offer satisfactory accuracy outdoors, their performance decreases in hybrid environments, such as in GNSS-challenged/denied environments, and is impractical indoors. In addition, a seamless transition between outdoor to indoor positioning systems is crucial. This paper has two main objectives: (1) creation of a framework to characterize and model RF (Radio Frequency)-based ranging observables from various radio localization technologies using empirical models; and (2) to design a methodology for collaboratively localizing groups of autonomously moving nodes, such as pedestrians. This is achieved by utilizing data from rover units, on-site fixed devices like Wi-Fi (Wireless Fidelity) Access Points (APs), and neighboring rovers. For the estimation and validation, this paper also includes the development and implementation of assessment procedures for performance evaluation. It assesses RF-based technologies through controlled experimental trials, analyzing range observable errors from Ultra-wide Band (UWB) and Wi-Fi Round-Trip Time (Wi-Fi RTT) technologies. The analysis provides insights into each technology's performance under different conditions and suggests techniques for range error mitigation. A key aspect of this evaluation is trueness, a quality metric that quantifies how closely the estimated position aligns with its actual (nominal) value. The methodology for collaboratively localizing groups of users combines UWB and Wi-Fi RTT systems, leveraging their complementary strengths. By integrating pre-existing Peer-to-Infrastructure (P2I) ranging infrastructure with ad-hoc Peer-to-Peer (P2P) ranging, this combination enhances coverage and flexibility for indoor positioning. By calculating standalone positions using existing infrastructure and combining them with UWB ranges and orientation observables, the collaborative positioning (CP) system improves accuracy and availability without extensive infrastructure. Localization algorithms are tested with field and simulated datasets to evaluate performance.

The paper is structured as follows: After the introduction, section 2 presents the research questions and objectives as well as the methodology for resolving them. In the following, the range-based CP approach is introduced in section 3 and then range correction models in 1D and 2D are discussed in section 4. Section 5 then introduces the position computation algorithm and section 6 the data correction and the error mitigation. Before the conclusions and outlook in section 8, section 7 deals withe the position estimation in the CP framework.

2. Research Objectives and Methodology

The main research questions and their primary and secondary objectives of this research can be summarized as: (1) to develop and test a methodology for identifying and mitigating errors in TWR (Two-way Ranging) RF range observations by conducting methodical field tests in controlled environments to examine TWR RF range errors; (2) to develop and test a robust, RF range-based positioning approach for groups of pedestrians walking in dynamic environments considering the hybrid nature of TWR measurements where the proposed algorithm computes the standalone position of the moving nodes in question aided by the existing communication infrastructure; and (3) to establish and implement a unified Quality Control (QC) framework for the assessment of the correctness and efficiency of the proposed solutions.

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The research methodology followed in this study consists of three distinct but interrelated implementation steps: (1) the range measurements calibration and correction phase which includes: (a) the pre-analysis stage, (b) the correction models development, (c) the error mitigation and models validation and the (d) kinematic range error correction; (2) the positioning algorithms development which includes: (a) the tuning of the positioning filter, (b) the collaborative positioning algorithms and (c) the cross-correlation effect mitigation; and the QC of the positioning engine utilizing real datasets which includes: (a) the field testing campaigns, and (b) the performance evaluation.

Following these strategies and developments, a suitable positioning system is developed for further refinement. The impact regarding the development and systematic evaluation of empirical range error correction models for UWB and Wi-Fi RTT can be summarized as: (1) development and implementation of spatial (2D) error corrections models for RF-based technologies; (2) introduction of orientation and RSS (Received Signal Strength) information within the corrections models; and (3) detailed and systematic performance evaluation of the proposed correction models leading to corresponding variations for both UWB and Wi-Fi RTT technologies.

In addition, the originality regarding the development and implementation of the pedestrian indoor CP algorithm refers to: (1) the combined use of Wi-Fi RTT and UWB in order to provide a balanced solution by utilizing the strengths and restrictions of each technology correspondingly; (2) the ability of the algorithm to operate efficiently while a minimum number of anchor nodes is available for short periods by optimally combining P2P (Peer-to-Peer) range measurements between the rover nodes in the CP network; and (3) the utilization of a range/heading Split Covariance Intersection Filter for UWB/Wi-Fi-RTT/IMU loosely coupled fusion in order to provide robust indoor positioning for groups of pedestrians.

3. Range-based Collaborative Positioning (CP)

In this section, a brief background summary on the basic techniques, the measuring principles and mathematical fundamentals for indoor CP determination using range observables is given. Inter-nodal ranging may refer both to range measurements originating from roving nodes to static anchors as well as between roving nodes. A description of the useable positioning techniques and methods as well as optimization algorithms in positioning and sensor fusion is omitted as it can easily found in the literature.

3.1 Range Error Identification and Mitigation

Obviously it is important that the raw observables (ranges, directions, etc.) have to undergo through decisive pre-processing to mitigate gross and systematic errors, see e.g. (Hao et al., 2018). Especially, in the indoor and GNSS-challenged/denied environment which are characterized by NLOS (Non-Line-of-Sight) conditions and severe signal multipath, the raw range observables can be of very low quality. Therefore it is important to study the nature of RF-based range errors and model their behavior aiming at minimizing their effect on the final position solution. Ranging errors may be handled either through theoretical modeling (e.g., probabilistic approaches handling random errors) or through empirical modeling (e.g., geometric approaches handling systematic) of observable-specific characteristics. Various research efforts have focused on methodologies aiming at mitigating NLOS effects (Wann and Hsueh, 2007), (Venkatesh and Buehrer, 2007). The distinction between LOS (Line-of-Sight) and NLOS observables can rely either on sequential range estimation and for outliers' thresholding or on channel statistics (Shijie and Dan, 2014). Studies suggest that the non-Gaussian distribution nature indicates a challenge when working with Kalman Filter (KF) algorithms since they assume that the measurement errors follow a Gaussian distribution (Conti et al., 2012). Especially indoors the distribution is of mainly non-gaussian TWR (Two-Way-Ranging) observations nature. This limitation usually is attempted to overcome with the adoption of non-linear measurement error models leading usually to particle filters (PF) (Gentner et al., 2012), (Ganti et al., 2014). The PF solution, however, leads to an increased computational complexity which is not easy to support by handheld, low-cost positioning systems. Alternative approaches include realizations of hybrid KF implementations based on pseudo-position measurements that could handle non-Gaussian error models (Li et al., 2016). These approaches still require increased processing power. As an alternative, the non-linear nature of the range error observables can be treated as a Gaussian Mixture (GM) filter type. Such filters can handle error distributions with multi-peaks applying multiple Gaussian models to approximate the complex nature of the transmitted signals (Muller et al., 2014). While this approach offers increased positioning accuracy for highly noisy measurements, its computational complexity increases dramatically for multi-node, range-based positioning. It is noted that while the KF approaches reach their limit in highly non-linear cases, still the EKF (Extended KF) offer a viable alternative when handling moderately non-linear error models due to their computationally efficient architecture (Wang et al., 2020).

The use of empirical RF range error models, on the other hand, relies on the systematic collection of real range observables to extract meaningful statistics that describe adequately their nature and extract range variation behavior that might be encountered during real-life localization applications. Examples of empirical modeling include an approach where asymmetric, double exponential ranging error distribution model are employed (Li et al., 2015). Here, the error model is formulated through fitting real data whereas an extension of tuning further the suggested model using range-based parameters is proposed. For that purpose, a Ranging Quality Indicator (RQI) can be estimated based on UWB signal characteristics paired with the corresponding ranging error used to train a Machine Learning (ML) algorithm (Jing et al., 2015). The algorithm produces a set of RQI values in real-time, and dynamically assigns weights to the range measurements in a UWB/IMU PF. In a study by Koppanyi and Toth (Koppanyi and Toth, 2014) the original UWB ranges histograms are found to present multiple peaks attributed to multipath effects. To overcome this effect, a Maximum Likelihood Estimator (MLE) is used for selecting the ranges with the highest probability of true values based on a comparison against the lateration-derived coordinates. Moreover, other empirical error models use range and position-dependent corrections produced using curve-fitting approaches on real data (Orfanos et al., 2023). In a further study by Toth et al. (Toth et al., 2017), range error calibration is implemented based on a grid of calibration points used for the generation of an ad-hoc model. Then the calibration values are used for the 2D linear interpolation forming the calibration function.

3.2 Collaborative Positioning (CP)

The increased necessity for CP systems comes both from the technological developments for utilizing optimally P2P communication as well as from the need for the minimizing the costs of permanently installed infrastructure (i.e., anchor RF transceivers) used by traditional RF-based positioning systems. P2P communication between nodes is based on technologies that can also offer relative ranging such as Wi-Fi, UWB and Bluetooth (Goel et al., 2016). CP implementations can make use of them both for application-specific data transmission as well as for supporting localization needs. The network architecture of a CP system can either be a centralized or distributed one (Goel, 2017). In a centralized architecture (Jing et al., 2016), (Masiero et al., 2023), as the name suggests, the positions estimation is performed centrally by a localization engine typically located at a control center that collects data from all the remote nodes. Central processing translates at increased processing power considering that state (position, orientation, velocity) computation of all nodes in the network is undertaken by a single processing engine. This approach leads to increased communication requirements as the information from all nodes in the network needs to be transmitted to the central unit. Notwithstanding an appropriately designed and implemented centralized CP engine offers high accuracy pose estimation for all nodes and inter-nodal state correlations it suffers decreased robustness. On the other hand, distributed CP architectures depend on their ability to self-estimate nodal positions based on the measurements and information collected within the CP network (Zhu and Kia, 2018), (Han et al., 2020). In order to achieve this goal, each node in the network needs to be equipped with a portable processing unit and certain communications infrastructure. The most crucial weaknesses of the distributed CP approach, however, are their inability to maintain inter-nodal correlation at network level leading to decreased mitigation of inter-dependent errors.

4. 1D and 2D Range Correction Models

Section 4 presents the methodological framework for the development of range correction models based on the statistical measures obtained using UWB and Wi-Fi RTT observables. An 1D and a 2D fitting model are proposed and implemented. Furthermore, model validation procedures are established. Following previous studies, the correction process for TWR data could be based either on empirical radial corrections applying a least squares line fit to the range deviations as a function of the distance or using a 2D range deviations plane fit (Toth et al., 2017), (Perakis and Gikas, 2018). In this study we examine both approaches and extend the examination to WILD Wi-Fi RTT data in order to select the appropriate correction technique that suits the corresponding data-set.

4.1 Radial 1D Fitting Model

The development of a radial 1D range correction model assumes the collection of TWR data at known reference distances with the chosen RF devices. Then for each pair of ranging devices a set of range measurements are collected to estimate their statistics and their deviation from the reference value. The type correction models usually adopted are the "mean", the "linear" and the "polynomial" (in the 2nd order) fit.

4.2 Spatial 2D Fitting Model

The two-dimensional range correction approach is based on the same underlying principle as the 1D approach. Here, the differences between the measured and true (reference) ranges are used for the generation of a correction database connecting the correction points. Thus, this approach takes into account the spatial distribution of the test ranges in the whole area of interest and provides a bi-dimensional correction fit which accounts for the location of each correction point. For the necessary interpolation the natural neighbor interpolation is used (Sibson, 1981), which is based on the Voronoi tessellation method. This Voronoi-correction approach is denoted as "vc" in this paper. For the area found outside the polygons defined by the correction points, linear extrapolation is performed in order to extend the Voronoi correction values.

4.3 Orientation-assisted Range Correction Models

4.3.1 Orientation Assistance Due to NLOS effects generated by physical obstacles or multipath, the model has to mitigate these effects in the TWR ranges. For that purpose, orientation assisted range error modeling is conceptualized and evaluated. In the case of pedestrian holding a mobile device, the user's body is acting as an obstacle which has to be accounted for by measurements in all four cardinal orientations, i.e., North, East, South, West. According to the rlc correction model, this approach generates a linear approximation of the correction values for each orientation. The expansion of the spatial (2D) correction model by the orientation assistance is proposed and termed as the orientation-Voronoi-correction model (ovc).

4.3.2 RSS-based Orientation Selection In order to apply the correction models discussed in section 4.3.1 in real case scenarios user orientation should be known. This can be obtained by the MEMS IMU embedded into mobile devices. The implemented approach relies on two facts and assumptions: (1) on the provided data of each RF-based conversation, including both TWR observables along with signal quality information (RSS), and (2) on the hypothesis that the main source of RSS fluctuation for an otherwise static rover is the change of orientation due to the imposed NLOS conditions. Then user orientation estimation relies on the comparison of the collected real-time RSS values against those obtained from previously collected RSS values for consequently selecting the appropriate orientation-based correction model. For this purpose, the correction database is also populated with RSS-based linear and bi-dimensional models that are generated in a similar manner as described above.

4.4 Range Correction Models Validation

In order to evaluate the appropriateness and operational efficiency of the range correction models, certain validation approaches are implemented. At a first stage, correction model validation refers to static ranges aiming at computing detailed statistical measures, whilst at the same time providing initial feedback for adopting a suitable correction model for the kinematic case. The second stage deals with the model validation process intended for kinematic positioning; specifically, for evaluating range error mitigation effects under realistic positioning scenarios.

4.4.1 Internal and External Parameters Affecting TWR Quality Due to inherent characteristics of the TWR observables and indoor environment conditions which is of prime interest in this work, several factors need to be accounted at model validation stage. Internal factors effect refers to the varying setups the TWR sensors may provide to the user such as different signal transmission configuration values and sampling

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rate. The choice of signal transmission configuration parameters such as signal bandwidth or Pulse Integration Index (PII) affects ranging performance. On the other hand, external effects refer to variations in the environmental conditions when performing TWR positioning. The indoor environment complex geometry, the presence of surrounding obstacles (static or mobile) as well as user body as such acting as the main source of NLOS, are some of the determinant external factors. In addition, RF signal attenuation, scattering and fading needs to be accounted for and evaluated within a validation procedure. The different TWR technologies adopted in this research are expected to provide a somewhat varying performance in varying environmental setups. Therefore, a detailed analysis takes place in order to gain insight that will facilitate subsequent experimental evaluation of positioning using a combination of the technologies.

4.4.2 Validation Procedure of the Static Range Correction Model The validation of the static range correction model presupposes a series of suitable range datasets collected at different observation distances. They are collected at the same environment as the correction datasets, since the ad hoc error correction models suit for the similar environmental conditions. The performance assessment of the range correction models at variable environments, however, exceeds the scope of this paper. Naturally, the evaluation of the validation datasets is performed on data collected specifically for validation purposes and not on those collected for error modeling. The number of validation points selected ranges between 30 to 40% of the total datasets points which is adequate for providing reliable evaluation results. The radial and spatial correction models and associated software are implemented as described in the sections above. Subsequently, the corrected ranges are cross-compared against the nominal distances resulting in a statistical evaluation, i.e., using trueness, mean and standard deviation.

4.5 Validation Procedure of the Kinematic Range Correction Model

Since the aim is to enable a correction model for kinematic (and/or dynamic) range evaluation for real-time applications, the validation procedure needs to expanded. Usually, the estimation of a reference trajectory relies on the realization of a predefined path along previously established and accurately surveyed points. Positioning performance evaluation relies then on the comparison of the estimated trajectories performance using the different correction models. Moreover, the assumptions underlying each model implementation is different as the radial (1D) models relies only on the measured range, while the spatial (2D) models relies on the previously estimated position. This validation step allows for the evaluation of the model implementation in real TWR data-sets intended for trajectory estimation. Trajectory quality metrics estimated against the reference trajectory enable the quantitative comparison among varying models.

5. Position Computation Algorithm

The development and evaluation of a suite of decentralized CP algorithms to enable the localization of multiple rovers using RF-based TWR observables collected in a network of roving and static nodes architecture is the ultimate goal of this work. The absolute localization engine which is experimentally evaluated in this study relies on an EKF realized in a collaborative manner. The architecture enables to optimally combine Pedestrian-to-Pedestrian (P2P) range measurements in a decentralized manner based on Split Covariance Intersection (SCI) grounds using the inter-device TWR ranges, the advertised rover state and covariance information. In addition, the observation setup relies on the provision of TWR observables from anchors of known coordinates to the rover in a dynamic manner using P2I ranges. The range measurements are then processed sequentially upon recording along with the reported accuracy (as estimated by the device) and the system timestamp. In a scenario of multiple rovers, each rover utilizes independently its corresponding measurements as they become available(Perakis et al., 2024). While the SCI-based approach ensures robustness in information fusion by avoiding overconfident estimates, its computational complexity remains a concern, particularly for low-cost mobile devices with limited processing power. Efficient implementation strategies, such as selective update mechanisms or computational load balancing, may be required to maintain real-time feasibility without compromising localization accuracy.

5.1 Correction Models Adopted for the UWB and Wi-Fi RTT Range Observables Internal Accuracy

Preliminary examination of the relationship between the RSS values logged for the Compulab © WILD units against the estimated ranging trueness values indicates the existence of a correlation. Moreover, the discrepancy between the reported Standard Deviation (SD) values and the TWR measurements trueness leads to low range quality indicator integrity. The trend in the correlation is analyzed further translating to a linear approximation of the standard deviation of range trueness against the RSS values leading to the diagrams of Figure 1.

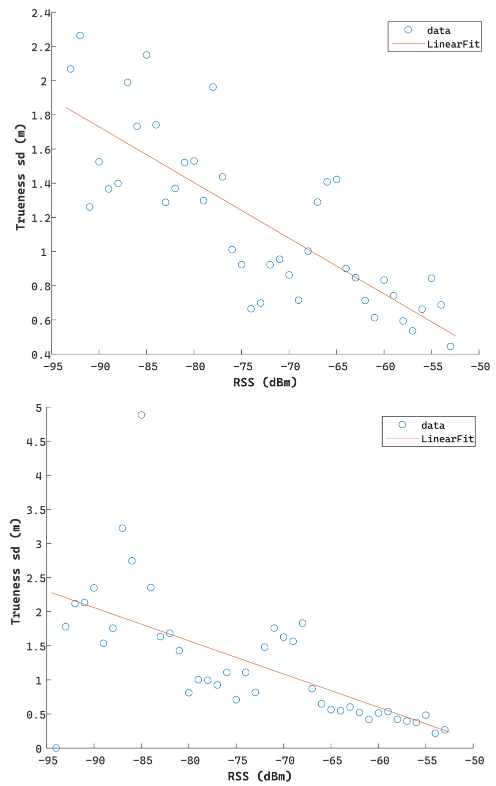

Figure 1. Examples of empirical trueness SD versus RSS values for Wi-Fi RTT observables.

6. Data Collection and Error Mitigation

In this section the procedures adopted for the generation and collection of simulated and field range data respectively for testing the proposed positioning algorithms are introduced. Also, the section presents the experimental evaluation procedures and techniques used for error mitigation.

6.1 Test Data and Equipment

The experimental campaigns include data collection undertaken both outdoors and indoors. Outdoor campaigns serve as early-stage feedback of the performance of TWR technologies examined in this work while at the same time provide a basis for the planning of the indoor experiments. Performance assessment of the range correction models is implemented both for the UWB and Wi-Fi RTT sensors on static as well as kinematic data. In addition, testing with simulated datasets is performed as it enables the generation of controlled and realistic TWR datasets in a systematic manner facilitating the development and optimization of the proposed CP algorithms.

The UWB system employed for field testing in the campaigns is the P410 module by Time Domain®. For Wi-Fi RTT, the Compulab ® Wi-Fi Indoor Location Device (WILD) modules are utilized. The employed Android smartphone devices support the Wi-Fi IEEE 802.11mc protocol. For the first campaign the Wi-Fi RTT observables were collected using a Google Pixel 2, while for the second campaign Google Pixel 3a XL. The second device was also utilized for the collection of azimuth values based on the embedded MEMS IMU (accelerometer, gyroscope and magnetometer) sensors. During data collection, the Android 9 operating software was installed on both smartphones.

6.2 Outdoor Field Test Campaigns

6.2.1 UWB Operational Range Assessment This campaign aims to investigate the maximum operational range of the Time Domain® P410 UWB modules in optimal environmental conditions. The selected test site is a coastal area in Faliro, Attica; Greece, where unobstructed LOS conditions are possible over a large inter-node distance (approx. 700 m). Notwithstanding, the maximum examined distances do not pertain to the typical application categories targeted in this work, the investigation of the equipment limits provides useful feedback for the overall potential of the employed equipment. Two UWB units are fixed on compatible camera tripods facilitating installation and transportation to each respective position. Inter-node reference distances are determined using the geodetic total station Topcon GPT 3107N for distances greater than 10 m whereas shorter distances are carefully measured using a measuring tape. Using the embedded range correction functionality of RangeNet® software (SW) the UWB pair-wise range error is mitigated by estimating the mean bias value at a reference distance of 5 m. Notably this functionality is available only for pairwise range corrections.

6.2.2 UWB Range Error Correction and Trajectory Estimation This experimental campaign aims at the preliminary evaluation of the UWB range error models for the static and kinematic case. The test area selection is based on the availability of ample space for the kinematic section, unobstructed ranging among UWB nodes as well as the unobstructed sky visibility for the establishment of GNSS/INS reference trajectory. A parking lot area located adjacent to the NTUA campus meets the aforementioned requirements. Ranging is performed among five UWB nodes four of which are utilized as static anchors of known locations. The fifth node is installed using a dedicated base on the roof top of a vehicle equipped with the Novatel® SPAN GNSS/INS reference trajectory equipment. The use of vehicle enables the generation of a high accuracy reference trajectory, as it offers a controllable platform for safely and accurately installing the reference equipment. Notwithstanding the trajectory of a vehicle varies substantially from pedestrian motion characteristics, this field test provides initial feedback for the effectiveness of the correction models in a systematic manner. The vehicle-mounted sensors’ lever arms are measured beforehand for implementing the required offset compensation whereas the static anchors’ locations are estimated using classical field surveying methods. In the kinematic session of correction model estimation, the correction points are established by performing the stop-and-go procedure at certain positions in the test areas. The estimated GNSS/INS positions for the stop-and-go points are used for computing reference rover-anchors ranges while at the same time UWB datasets are collected. Inter-nodal ranging is performed between all UWB pairs (both static and kinematic) for which a TDMA slot map covers all conversations at a cycle sampling rate of around 5 Hz.

6.2.3 WiFi-RTT range correction and trajectory estimation At a preliminary stage, experimental evaluation of the Wi-Fi RTT ranges took place at the rooftop of Lampadario building of the School of Rural, Surveying and Geoinformatics Engineering (SRSGE) of the NTUA, Zografou Campus, Athens, Greece. For the stage of static 1D ranging, three WILD APs are successively mounted securely on a geodetic tripod (with a known height) whereas the Android device Google Pixel 2 is placed sequentially on the other end of reference distance. The selected reference distances are realized at 1, 2, 5, 10, 15, 20, 25, 30, 35 and 45 m, exceeding the nominal effective range of 40 m as reported by the manufacturer. The smartphone is installed on a geodetic pole using a modified smartphone holder in order to ensure repeatable placement over the reference points at a manually measured height. For each reference point a dataset of around 100 observables are collected, repeating the process for all three APs.

Concerning the kinematic positioning setup, three Wi-Fi RTT APs are installed over points of known coordinates and their height is measured at their anchor locations. The anchors are installed in an area arrangement that realizes multiple checkpoints preinstalled and accurately surveyed at a canvas pattern that may be utilized for checkpoint-based reference trajectory estimation. For data in kinematic mode a pedestrian carrying the geodetic pole with the smartphone moves along predetermined paths.

6.3 Range Errors Mitigation

The analysis of TWR observables using range correction models offers feedback concerned with the correctness of the proposed procedures as well for the potential of tested technology through empirical error mitigation. Both the UWB as well as the Wi-Fi RTT sensors are assessed.

6.3.1 UWB Outdoor Operational Range Evaluation Analysis The collected UWB range datasets are pre-processed in regard of logfile parsing and data grouping based on nominal distances and relative antennas orientation sets. The levels of accuracy and precision of the measurements are then calculated as a function of the distance and orientation of the antennas. Figure 2 shows the range deviation values obtained using the mean and median of the measurements respectively. The plots reveal a trend in range deviation from the reference distance as the inter-nodal distance increases. Also, it is evident that using the median offers significantly improved performance. Outliers can have a profound impact on the mean, distorting its true representation of the data. However, the median value remains robust in the face of such outliers, making it a more reliable measure in certain situations. These statistics provide useful feedback for the UWB range error mitigation campaigns. Finally, it is found that antenna orientation seems to affect the measurement accuracy at distances greater than 500 m. It is noted that the increase in values at 300 m for large relative antennas orientation is attributed to the existence of a parked vehicle close by the LOS between the receivers.

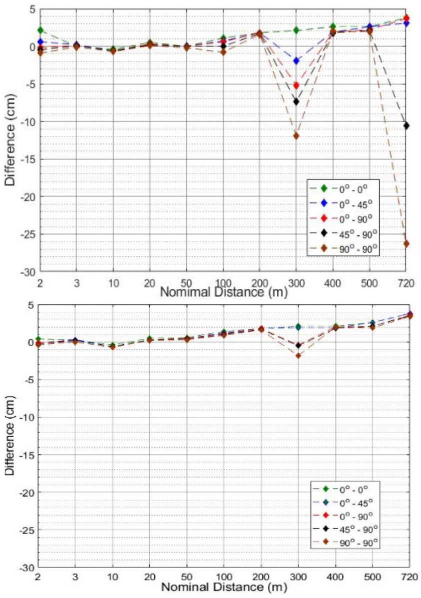

Figure 2. Range deviation estimation using mean and median values of UWB observables for campaign C0.1.

Figure 3 depicts the histogram of the observed range difference from its mean value. The high repeatability of the measurements is evident. Specifically, only few long ranges deviate from the mean with a 6 cm maximum difference. It is also noted here that the presented ranging results have previously undergone the pair-wise range correction procedure (as indicated by the manufacturer) prior data collection. Therefore, this analysis does not concern raw uncorrected ranging observables. Notably, the longest distance of 720 m in the experiment is confined by the size of the measurement area, and therefore, it does not represent the maximum operational range of the UWB system.

6.3.2 UWB Outdoor Range Error Correction Analysis In the static ranges error mitigation, data collection employed four anchor nodes and one rover. Range measurements were conducted among all anchors as well as from each anchor point to the rover. Measurements collected between anchors facilitate the assessment of distance correction process for multiple pairs of transceivers at fixed relative distances. Indicatively, Figure 4 presents the ranging samples, the average value, the median as well as the reference value both in the form of a probability density function histogram as well as a timeseries. Table 1 summarizes the range statistics (mean and median) from the nominal distance for all anchor pairs. Apparently, from Table 1 a range bias is evident as the range correction procedure using Time Domain® software cannot compensate for the total network corrections. The values in the Table for the median are utilized as pairwise correction values. This is due to the absence of relative distance changes for anchors, making it impossible to estimate a more complex range error model. Conclusively, the median is chosen as it best approximates the value recorded by satisfactorily ignoring outliers. By implementing a least-square adjustment for the anchors network, the determination of local coordinates using UWB measurements is possible. To solve the 3D grid, the following constraints are considered: Point 101 position is held fixed, height values are constant as measured at the test site, and point 102 is supposed to lie on the X-axis (y101 = y102). Therefore, the independent determinants of the model are [x102, x103, y103, x104, y104]. The process of the Weighted Non-Linear Least Squares (WNLLS) method is repeated to cover the entire dataset. Table 2 presents the deviation in ranges between the WNLLS solution and the reference distances for the cases before and after range correction. The effect of range correction on resulting ranges is evident resulting in maximum deviation of 1.3 cm.

	Deviation	
UWB nodes pair	mean	median
101-102	0.368	0.367
101-103	0.352	0.351
101-104	0.355	0.355
102-103	0.741	0.741
102-104	0.741	0.734
103-104	0.752	0.742

Table 1. Anchor pairs UWB range deviation in [m] for campaign C0.2 before range correction.

	WNLLS ranges deviation	
UWB nodes pair	uncorrected	corrected
101-102	0.204	0.002
101-103	0.282	-0.002
101-104	0.422	0.005
102-103	0.803	0.001
102-104	0.697	0.013
103-104	0.604	-0.013

Table 2. Anchor pairs UWB range deviation in [m] after WNLLS implementation using both corrected and uncorrected ranges for Campaign C0.2.

The correction of UWB kinematic measurements based on the stop-and-go points is implemented using 3 different empirical models: the mean value, the linear fit and 2nd degree polynomial fit (see section 4.2). The models are implemented radially around each fixed transceiver, utilizing the varying deviation values from the reference distance for each pair and distance. Corrections are then applied based on the specific distance. Figure 5 (left) presents the results obtained from the three models whereas Figure 5 (right) presents the correction values obtained for transceiver 103 (red point – top left) displayed in the form of contours. In this plot the magenta points refer to the stop-and-go points. The different range error models' effectiveness is evaluated during the kinematic trajectory estimation.

6.3.3 WI-Fi RTT Outdoor Range Correction Analysis The pre-processing stage concerned with the static Wi-Fi RTT observables aims at range reduction from sloped to horizontal and data grouping. Figure 6 presents the histogram of the range differences from reference value for all APs for a nominal distance of 5 m. Notably, the standard deviation of each series of observations does not exceed 0.3 m except in very few cases. As

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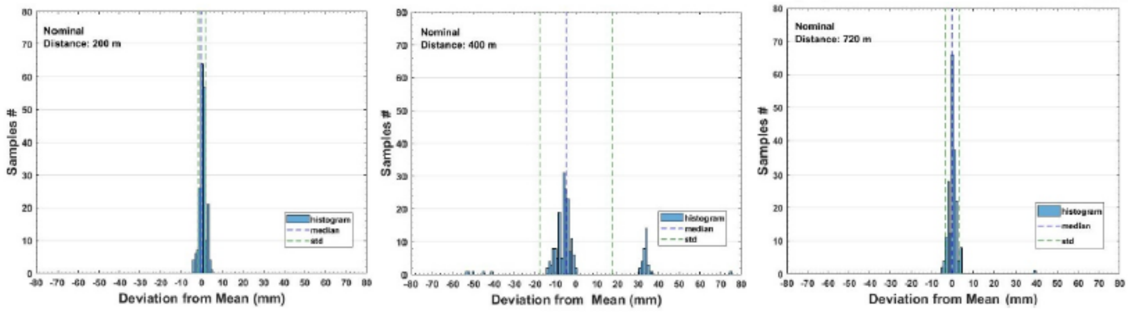

Figure 3. Histograms of UWB ranges deviation from the mean value for nominal distances 200, 400 and 720 m of Campaign C0.1.

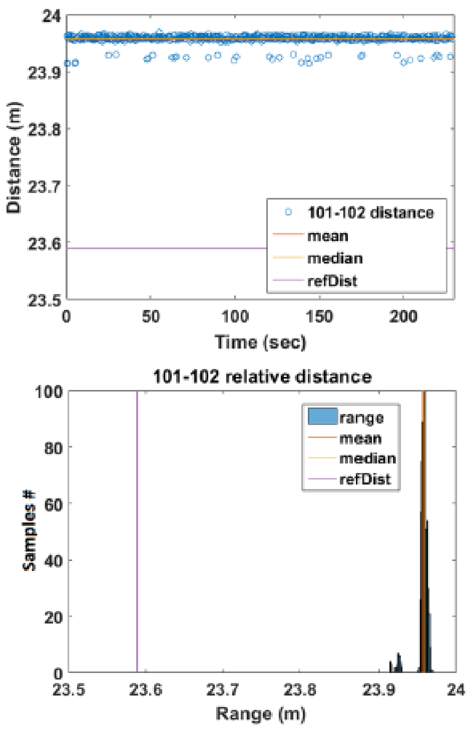

Figure 4. Ranging measurements among anchor UWB nodes 101-102 during campaign C0.2 kinematic ranging section. Timeseries (top) and frequency histogram (bottom).

indicated in Figure 7 regarding AP1 data, range trueness for reference distance 20 m and 25 m exhibits an increase reaching a maximum value 1.2 m. In addition, signal strength value shows a drastic drop for ranges up to 15 m (approximately from -45 to -65 dBm) and a milder drop for ranges 15 to 45 m (about -65 to -75m dBm). The reported standard deviation values suggest stability, whereas the increase for the distance of 15 m suggests the potential of the system to identify ranging quality deterioration. Also, Figure 7 suggests that range observations for a nominal distance of 20 m have been contaminated by multipath originating from a metal structure located at the side of the ranging smartphone at distance of around 2 m resulting at increased deviation values. Moreover, it is observed that even at a nominal distance of 45 m, still there is no drastic reduction in accuracy implying that the system reaches maximum effecting range. The generated range error models are presented in Figure 8 for the cases of mean, linear and 2nd order polynomial approximation models. These results are produced using the EPD-Fmax values of the respective ranging datasets. It is noted that the values corresponding to distances of 10, 20 and 35 m are not utilized during models' generation in order to be utilized as validation distances. Table 3 summarizes the resulting statistics for the different correction models' implementation. Clearly, no drastic improvement is evident using the polynomial fitting compared to the linear fit, whereas at some cases the resulting values may even present lower accuracy. This is indicative of the potential over-fitting effect. The linear correction model is deemed sufficiently effective and is selected for the implementation of kinematic trajectory estimation as demonstrated in the following section.

	WNLLS ranges deviation (m)	
UWB nodes pair	uncorrected	corrected
101-102	0.204	0.002
101-103	0.282	-0.002
101-104	0.442	0.005
102-103	0.803	0.001
102-104	0.697	0.013
103-104	0.604	-0.013

Table 3. Statistics of range correction models effect on Wi-Fi RTT range datasets collected in in campaign C0.3 for the three validation distances.

7. Position Solution Estimation

This section presents the experimental results obtained for the position solution using the standalone positioning using UWB P2I algorithmic approach and the data sources detailed in the previous section. The evaluation of the proposed positioning techniques for non-collaborative rovers relies both on simulated and field data. he evaluation of the CP scheme, due to hardware limitations and adversities, relies only on extensive simulated datasets generated suitably for multiple, simultaneously operating rovers in varying availability conditions.

The trajectory obtained for a single rover using field test UWB data (Campaign C0.2) relies on a constant velocity EKF. In total, four variations are produced for the rover trajectory. Three of them implement the range correction models introduced above ("mean", "linear approx." and "polynomial approx.") and the fourth one represents the uncorrected (raw TWR data) position solution. Figure 9 illustrates a typical example of the vehicle trajectory for the linear correction model, accompanied by the coordinate timeseries of the along-track and off-track trueness values. Increased trueness values are observed for the along-track estimates with values approaching 2 m. The improved solution mainly for the cross-track trueness indicates the weakness of the employed EKF dynamic model selection, as it is specifically configured for pedestrian positioning. Expansions

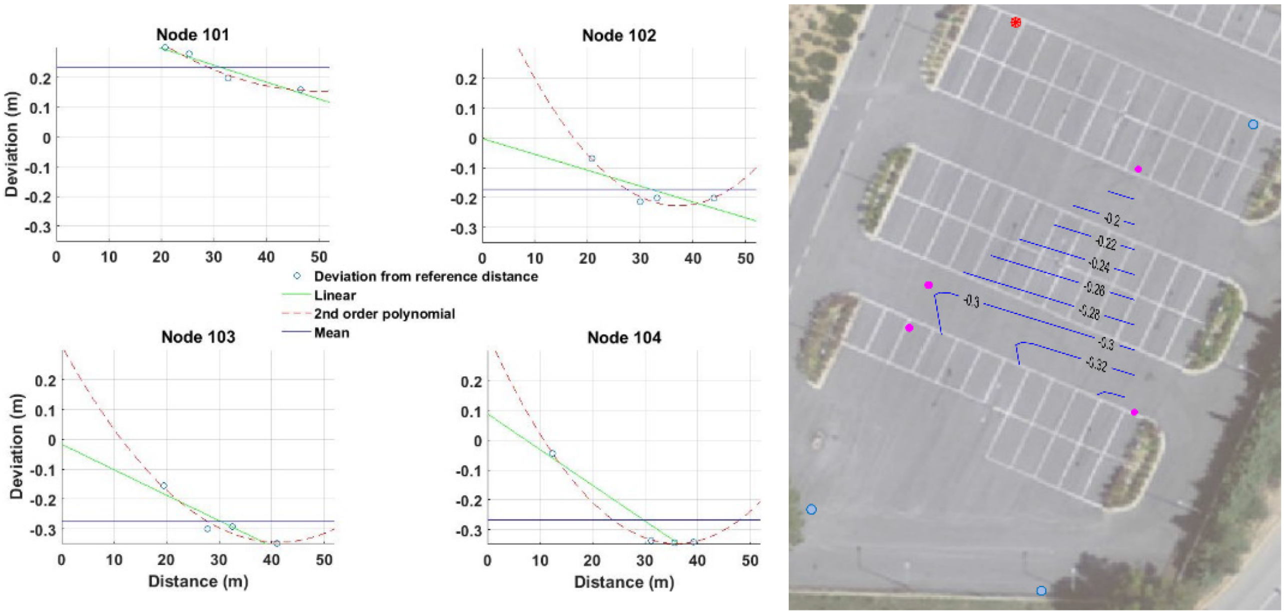

Figure 5. Rover-anchors error correction models with respect to the measured distances, range error contours for UWB node anchor 103 for Campaign C0.2.

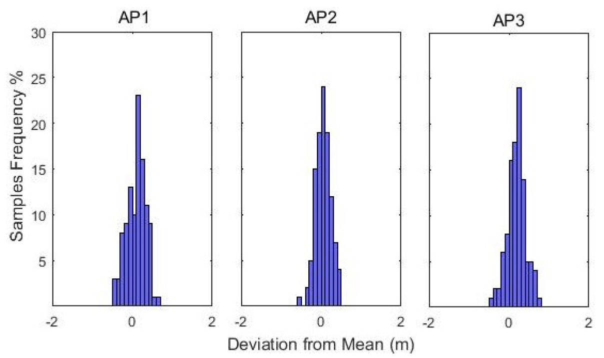

Figure 6. Histograms of ranges deviation from the mean value for the nominal distance of 5 m for the three different Wi-Fi RTT APs of campaign C0.3.

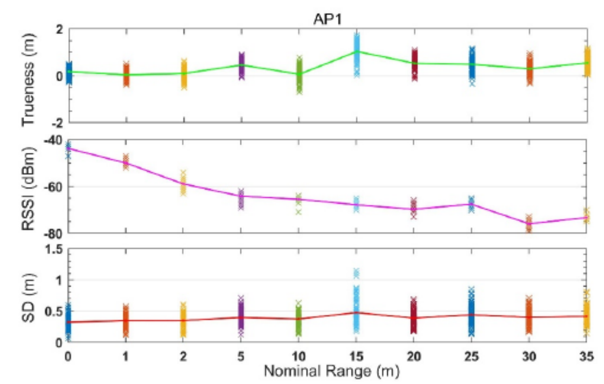

Figure 7. Range trueness, signal strength and SD values for the nominal distances of campaign C0.3 for Wi-Fi RTT AP1.

of this work aiming to tackle TWR-based vehicle localization may implement appropriate filter tuning procedures for compensating for vehicle kinematics.

8. Concluding Remarks and Outlook on Future Work

Two key objectives are attained through the proposed methodologies presented in this study. Firstly, to develop a methodology for performing quality characterization and assessment of UWB and Wi-Fi RTT TWR observables that enables the systematic range error mitigation through empirical correction models. Secondly, to develop and test an algorithm for collaborative positioning of multiple kinematic nodes based on a combination of UWB and Wi-Fi RTT ranges, using both P2I and P2P observables. Figure 10 summarizes the performance statistics for UWB and Wi-Fi RTT kinematic positioning obtained utilizing the main empirical range error model categories (i.e., "no correction", "linear correction" and "spatial correction") for the entire field data available. The respective trueness values (mean and standard deviation) accompanied with their associated availability measures, showcase the different accuracy metrics obtained and underline the need for appropriate model selection. For the UWB data, an improvement of 62% is apparent for the mean trueness using the "linear correction" and 74.3% accordingly for the "spatial correction" model. Evidently, an improvement of 55% results in the standard deviation values for both correction models. No availability issues are identified for the UWB data which is expected given the specifications of high sampling rate, accuracy and communication stability. Regarding Wi-Fi RTT data, an improvement of 54.1% is apparent for the "linear correction", whilst the "spatial correction" models lead in worse performance both in terms of trueness mean and standard deviation values. This is attributed to the noisier nature of the Wi-Fi RTT observables that make the more complex nature of the "spatial correction" models more prone to inaccuracies and extreme values. Nevertheless, in order to reach an impartial characterization of systems performance, it is important to study range availability values simultaneously with trueness. Notwithstanding, the Wi-Fi RTT "no correction" case falsely reports better performance when only trueness is taken into account, its corresponding availability measures are reported to be 21.8% of the total sample, whilst the "spatial correction" case reads a valid solution at 52.4% of the sample. Overall, the selection of the appropriate cor-

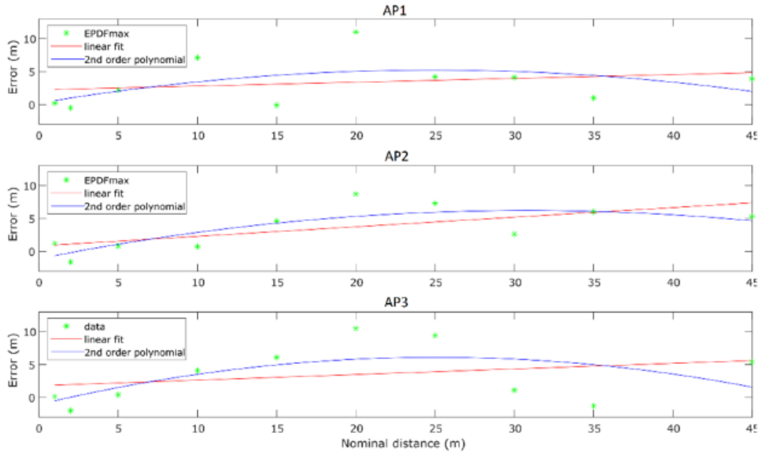

Figure 8. Correction models estimated for the three different Wi-Fi RTT APs of campaign C0.3.

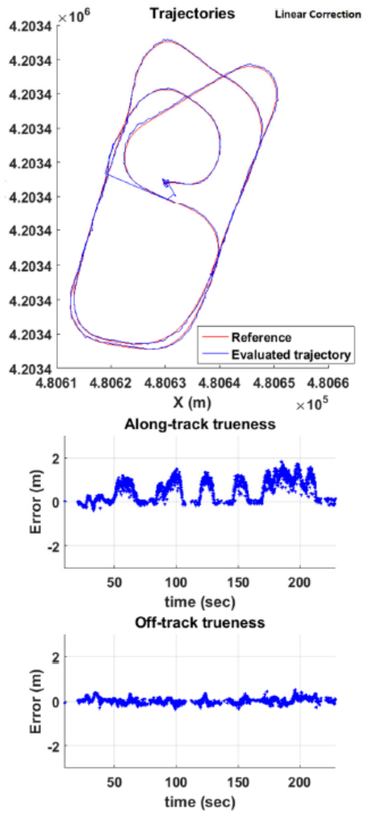

Figure 9. Vehicle trajectory (top) and position trueness along-track (middle) and off-track (bottom) time histories using UWB ranging assuming a linear correction model (Cam. C0.2).

rection model depends primarily on user-specific requirements as imposed by application type. In general, the "spatial correction" model is proven suitable for the more accurate UWB ranges, while the "linear correction" model deems suitable for both technologies.

Further enhancements of the system as well as the ability to further investigate the different variations of the proposed approaches enable future expansion. Firstly, evaluating the correction methodology in different test areas with varying LOS/NLOS conditions can further support its generalization ability. As the proposed range error evaluation approach can be expanded to virtually unlimited similar technologies, further evaluation with additional RF-based ranging datasets (i.e., low-cost UWB sensors) is suggested. The distributed collaborative architecture of the DCP algorithm ensures scalability and supports future implementation on mobile devices, making it suitable for various real-world applications such as urban navigation and disaster recovery. Notwithstanding that a great number of personal mobility applications rely directly on the positioning solution produced using a single device, a continuously increasing number rely on additional state information (orientation, elevation, etc.). Given the multi-sensory character of today's smartphones, numerous applications could benefit from the fusion of additional sensor data introduced within the loosely-coupled architecture of the DCP solution. For example, as UWB functionality is already available on several smartphones and given the cost limitations implicated by these mass-market devices, investigating the proposed approaches using low-cost UWB sensors would provide valuable insight regarding their large-scale applicability. Moreover, incorporating elevation data from barometric sensors or integrating indoor maps for map-matching could further enhance positioning robustness. Both rover self-localization improvements and the subsequent collaborative steps propagating quality improvements to neighboring nodes would benefit a potentially unlimited number of users.

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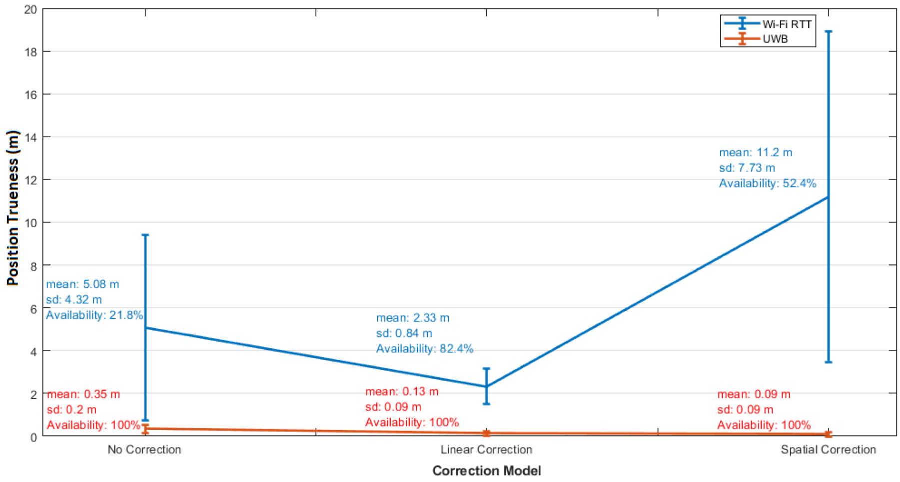

Figure 10. Statistical summary of UWB and Wi-Fi RTT range correction models performance.

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