Adding Link Quantity Information to Redundant RF Signal Strength Estimates for Improved Indoor Positioning

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***Abstract*—A common approach of range-based indoor positioning methods use the received signal strength (RSS) of RF packets from several anchor nodes to estimate their distances to a mobile emitter with unknown position. The range-based weighted centroid localization (WCL) approach with link quality information (LQI) is known to be more accurate than range-free centroid localization (CL) methods using only a binary radio link information according to the cell of origin (COO) principle. With the combining of redundant RF channels using spatial and frequency diversity the WCL position estimation is proved to be even more reliable, although the RSS-based distance estimations of a single RF channel are known to be error-prone in multipath indoor environments. A novel range-free approach using the exact number of available diversity channels – the link quantity information (LQnI) – is proposed. It needs no more infrastructural effort or processing power and can easily be applied to the range-based WCL estimation technique with redundant sensor information. Especially the combining of the redundant RSS-based distance estimations together with the LQnI approach leads to a more accurate position estimation. Experimental results in an office building and in a real-life tracking application for maintenance staff in the underground coal mining show the improvements of the additional range-free approach.**

***Index Terms*—Centroid Localization, Indoor Positioning, Link Quantity Information, Received Signal Strength, RF Channel Diversity.**

I. Introduction

The reliable positioning of people and materials in heavy-obstructed indoor environments is an ongoing and challenging research issue. Modern indoor local positioning systems (ILPS) show a variety of applied sensor technologies [1]. Typical evaluation criteria for a taxonomy of an ILPS are given in [2] together with the general characterization of an ILPS. A suitable way to compare the taxonomy of different systems is illustrated in Fig. 1. The main criteria are the accessible coverage and accuracy of the position estimations. An overview of the latest positioning systems with a comparison of their specific coordinate accuracy and coverage is given in [3]. The coverage also contains the system's performance in non-line-of sight (NLOS) scenarios. The accuracy is defined by the short-term position estimation error and the long-term stability of the system. Of course, also the costs for installation and maintenance of the system infrastructure should be taken into account.

The coverage of directional sensors like infra-red (IR) [4], ultrasound [5] or optical systems [1] is limited to line-of-sight (LOS) scenarios. Systems with artificial quasi static magnetic fields are more robust in multipath environments, although the high power consumption of coil-based artificial magnetic fields limits the application range [6].

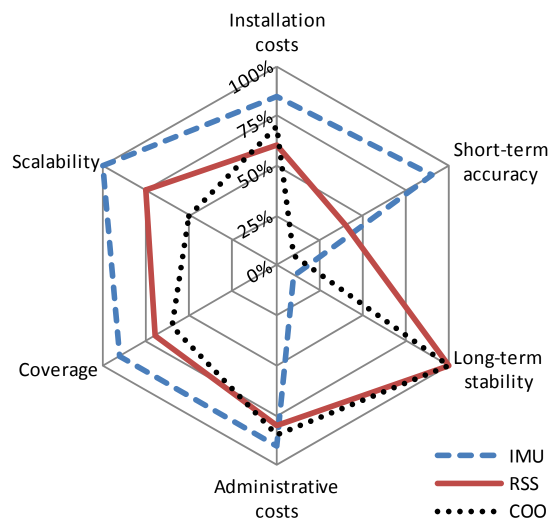

Fig. 1. Taxonomy of localization systems.

Due to the latest advances in micro-electro-mechanical systems (MEMS), the use of a miniaturized inertial navigation system (INS) using a MEMS-based inertial measurement unit (IMU) seems interesting for an ILPS. The main drawback of IMU-based systems is the limited long-term stability due to error propagation of the direction and distance measurements.

Range-based systems with an evaluation of the received signal strength (RSS) of narrow-band RF signals might also be used for obstructed environments with many NLOS conditions, although they are known to be error-prone in multipath environments [7],[8]. Nevertheless, RSS-based distance estimation techniques put low demand on the hardware and software complexity of the infrastructure components and thus, are widely distributed. E.g. the WLAN-based Horus system [9],

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RADAR system [10] or the commercial Ekahau location engine use RSS measurements. As shown in the taxonomy in Fig. 1, different approaches might have complementary characteristics looking at some of the criteria. In contrast to IMU-based systems, RSS shows no error propagation between two measurements and thus, the long-term stability of the accuracy is not an issue. Otherwise, in indoor fading environments, an IMU-based system can reach a better short-term position accuracy than RSS-based systems. In general, range-based systems like RSS are more accurate than range-free systems like the COO technique.

Hybrid localization systems with a sensor fusion of different types of sensors may overcome the specific drawbacks of a single system [5]. The fusion of RF-based systems with an INS is a common solution which offers both, a good short-term accuracy and a good long-term stability [11]. Of course, the improvements need additional hardware and software efforts. The proposed localization system uses a different approach where the combining of a range-free and range-based centroid localization system leads to more precise position estimates without any additional hardware or software efforts.

In section II, related range-based centroid localization approaches using single and redundant RSS measurements are compared. The basic range-free centroid localization is presented in section III together with a proposed enhancement for redundant radio links. In section IV, we propose a hybrid centroid localization approach which uses redundant range measurements and an additional range-free approach. In section V, the localization system performance is validated by experimental results of a dynamic measurement on a motion test track. In the last section VI, the results are discussed and investigated in terms of an outlook for further system developments.

II. Range-based Centroid Localization

A. Weighted Centroid Localization (WCL) using RSS Readings

The general weighted centroid localization (WCL) approach uses a link quality indicator (LQI) to get a more precise location information [12]. RSS readings are a common LQI which can also be used for distance estimations. According to the Log-distance model the distance dependent average path loss of RF signals is given with

$$\overline{PL}(d) = PL(d_0) + 10n\log\left(\frac{d}{d_0}\right), \tag{1}$$

where $\overline{PL}(d)$ is the average path loss over a distance d in dBm, $PL(d_0)$ is the reference path loss over a reference distance d_0 and n is the environment-specific propagation coefficient.

The value of $PL(d_0)$ is influenced by the effective radiated power (ERP) of the RF transmitter and the gain of the transmitting and receiving antenna. For the used IEEE 802.15.4 compliant proprietary $2.4\,\mathrm{GHz}$ ISM transceiver with an output power of $+10\,\mathrm{dBm}$ we have investigated a $PL(d_0)$ of $-67\,\mathrm{dBm}$ at $d_0 = 1\,\mathrm{m}$.

The value of n is influenced by the specific environmental propagation conditions and the used frequency. In [13] and [14], values for n between 1.8 and 3.2 are given for obstructed indoor environments and frequencies between $900\,\mathrm{MHz}$ and $4.0\,\mathrm{GHz}$.

In the first step of the WCL algorithm, the RSS values from all receiving reference nodes (RNs) are transformed into distances. Using (1), a reference path loss $PL(d_0)$ at a distance $d_0 = 1\,\mathrm{m}$ and the RSS instead of the path loss, the distance d_{ij} between the transmitting blind node (BN) and the j-th RN at time instance i can be calculated with

$$d_{ij} = 10^{\left(\frac{RSS_{ij} - RSS(d_0)}{10n}\right)}. \tag{2}$$

In the second step, the distances d_{ij} are transformed into weights w_{ij} according to (3).

$$w_{ij}(WCL) = \frac{1}{(d_{ij})^g} \tag{3}$$

Similar to the path loss coefficient n, the weighting factor g depends on the environmental conditions. From previous measurements in obstructed indoor environments the weighting factor was determined between 2.2 and 3.8 [15].

The BN's position is given by the weighted positions of the RNs. The accuracy depends on the subfield of the regarding area (center or border) and the relationship between relative and absolute LQI values. For low LQIs the BN might be located near a dominating RN (cf. Fig. 2). For high LQIs, the advantage of the weighting gets lost and the WCL reaches similar results to range-free centroid localization approaches which are discussed in the next section III.

In [16] we have proposed the selective adaptive weighted centroid localization (SAWCL) approach, which enables a further improvement of the accuracy by an adaption of the weights according to their statistical distribution. Looking at Fig. 2, for low LQIs all of the weights are raised by a specific fraction, for high LQIs they are reduced to increase the relative difference of the weights. The BN's two-dimensional position $P_i\,(x, y)$ at the time instant i is computed with the modified weights w'_{ij} and the fixed positions $B_j\,(x, y)$ of the RNs according to

$$P_i\,(x, y) = \frac{\sum_{j=1}^{m}\left(w'_{ij} \cdot B_j\,(x, y)\right)}{\sum_{j=1}^{m} w'_{ij}}. \tag{4}$$

B. WCL using Redundant RSS Readings (rWCL)

RSS-based distance estimations in multipath indoor environments are known to be error-prone. With a diversity configuration using more than one channel between BN and a single RN the multipath fading can be compensated and the error of the distance estimates is reduced significantly. Thus, the accuracy of the WCL position estimates is increased in a significant way.

If there exist more than one channel between the BN and a single RN, the RSS for the distance approximation is calculated using a maximum probability combining (MPC) algorithm [18]. With a diversity scheme like the one proposed in [16], up to four independent radio channels are available

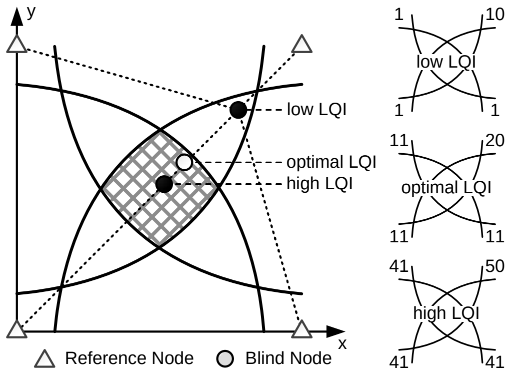

Fig. 2. Centroid localization approach showing the influence of the LQI distribution on the position estimation. Source: [17]

between the BN and a single RN. With the miniaturized hardware platform used here and described in detail in [18] even eight nearly independent RF channels are used. For m redundant diversity channels, the distance d_{ij} between the transmitting BN and the j-th RN at time instance i can be calculated with

$$d_{ij}(rWCL) = 10^{\left(\frac{MPC_m(RSS_{ij}) - RSS(d_0)}{10n}\right)}, \tag{5}$$

where $MPC_m(RSS_{ij})$ is the RSS from the j-th RSS which has the maximum probability out of $N \leq m$ acquired RSS values. The weighting factor w_{ij} and the centroid $P_i(x, y)$ of the BN's position are calculated according to (3) and (4).

III. Range-free Centroid Localization

A. Basic Centroid Localization (CL)

Centroid localization (CL) is a proximity based technique to determine the rough position of a BN with the help of certain RNs with minimum software efforts. The basic CL algorithm as a simple range-free implementation uses the binary link information of several RNs with known positions as sensor input for a rough location estimation [19]. In Fig. 2, a scenario with four RNs is shown. Under the assumption of entire uniform circular communication ranges, the BN is located inside the shaded area when it has a link to all four RNs. The position estimation is calculated according to (4) where the weights are given with

$$w_{ij}(CL) = \begin{cases} 1 & \text{, link to } j\text{-th RN} \\ 0 & \text{, no link to } j\text{-th RN} \end{cases} . \tag{6}$$

With the binary weighting factor only the RNs which have a link to the BN are used for the calculation of the centroid using (4).

B. CL using Link Quantity Information (rCL)

With a diversity configuration proposed in [18], an additional source of position information is available. Instead of using the RSS as LQI for a range-based positioning, a novel range-free centroid approach uses the exact number of available diversity channels – the link quantity information (LQnI) – to estimate the BN's position. Like for the WCL and basic CL, the position estimation is calculated according to (4). For the rCL algorithm using LQnI information the weights are given with

$$w_{ij}(rCL) = \frac{\#_{ch}(RX_{ij})}{\#_{ch}(MAX_{ij})}, \tag{7}$$

where $\#_{ch}(RX_{ij})$ is the exact number of available channels which signals could be received by the j-th RN and $\#_{ch}(MAX_{ij})$ is the maximum number of available channels.

IV. Hybrid Centroid Localization

The final hybrid centroid localization (rHCL) approach uses redundant RSS-based distance approximations $d_{ij}(rWCL)$ from (5) and the additional LQnI weighting $w_{ij}(rCL)$ given with (7). The rWCL approach compensates multipath fading effects and reaches more accurate position estimates than single channel WCL. It might be odd that the rough range-free rCL position estimate would improve the accuracy of the range-based rWCL positioning but in environments with a lot of reflecting surfaces, the LQnI sometimes is a better indicator than an RSS-based LQI. The following results from a real life tracking application are used to explain the behavior of the hybrid rHCL approach.

In Fig. 3, a typical setup of RNs for a one-dimensional localization and tracking of maintenance staff in an underground longwall coal mining environment is shown. The RNs are installed on heavy metallic shields for the ceiling support.

Fig. 3. Infrastructure components for RSS-based positioning and tracking of maintenance staff in the underground longwall coal mining environment (RN – reference node, BN – blind node).

In Fig. 4, the scheme of a one-dimensional infrastructure setup in an overground longwall mining training environment with twenty RNs and a distance of $1.5\,\mathrm{m}$ between the nodes is shown together with the estimated position of the mobile BN. The scheme shows the position estimation GUI of a proprietary Java framework (MineLoc Monitor v0.2) which was developed to evaluate the performance of different localization algorithms [20].

The LQnI values for two different frequencies ($868\,\mathrm{MHz}$ | $2.4\,\mathrm{GHz}$) are shown below the RNs, the RSS values are shown above the RNs. For the shown time instance the BN was located at RN 9. RN 18 has calculated an RSS value of $-75\,\mathrm{dBm}$ using the MPC approach. This value indicates a much smaller distance than the actual distance between BN and RN. Multipath fading with a positive signal interference of two or more RF waves at the receiving RN is the cause of this deviation. The estimated position using the rWCL algorithm was calculated between RN 9 and RN 10 with a positioning error of $0.38\,\mathrm{m}$.

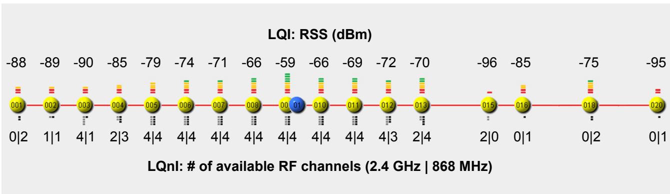

Fig. 4. One-dimensional localization for longwall mining setup with 20 reference nodes using LQI (RSS) and LQnI information.

The LQnI of RN 18, which is 2 out of 8, is the better sensor information in this particular case. This example acts as a motivation to make also use of the LQnI values for the position estimation, especially since there is no need in extra costs for hardware or computation time.

The processing steps are the same as for redundant WCL and basic CL. The distance approximations are calculated according to (5). The weighting factors are given with

$$w_{ij}(rHCL) = w_{ij}(rWCL) \cdot w_{ij}(rCL) = \frac{\frac{\#_{ch}(RX_{ij})}{\#_{ch}(MAX_{ij})}}{(d_{ij}(rWCL))^g}. \tag{8}$$

The effect of the additional LQnI information is illustrated in Fig. 5. The distribution of the RSS values over the 20 RNs is shown for two different approaches. Without additional LQnI information the relatively strong RSS values of RN 16 and RN 18 lead to an RSS distribution where the centroid is influenced by these values. When an additional weighting is introduced (LQI+LQnI), the influence of these two RNs is minimized and thus, the position estimation error is reduced.

When no channel is disturbed and thus, the number $\#_{ch}(RX_{ij})$ of received RSS values equals the maximum channel number $\#_{ch}(MAX_{ij})$, the numerator in (8) is reduced to "1" and the hybrid approach delivers a similar weighting factor as the rWCL approach (cf. Fig. 5, RN 5-11).

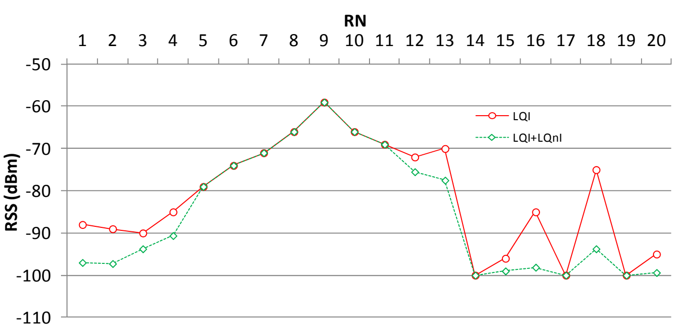

Fig. 5. RSS distributions over 20 RNs for longwall mining setup with and without additional LQnI processing ($1.5\,\mathrm{m}$ RN distance, BN located at RN 9).

V. Localization and Tracking Results

The test bed for the localization and tracking measurements under laboratory conditions is shown in Fig. 6 on the left. A

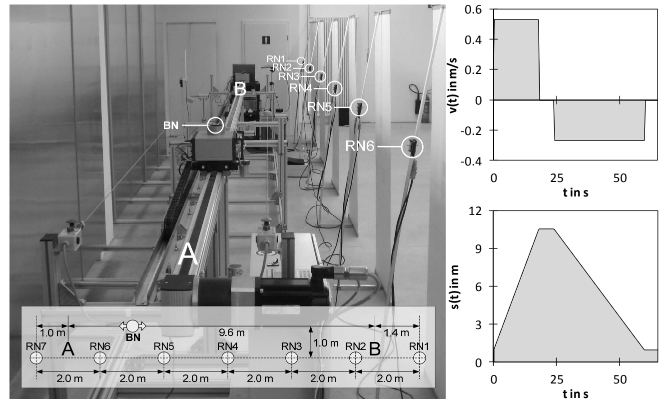

Fig. 6. Measurement setup on a motion test track in an obstructed test hall (motion profiles show one A-B-A motion cycle, $T = 65\,\mathrm{s}$).

motion test track in an obstructed test hall is used to figure out the impact of the redundant signal processing and the additional LQnI information on the positioning error. The mobile BN which should be located performs periodic movements on the motion test track according to the motion profile shown in Fig. 6 on the right. The duration of one movement from position A to B and back to A is $65\,\mathrm{s}$. Seven RNs are evenly distributed along the track with a distance of $2.0\,\mathrm{m}$ between two nodes. For an explicit multipath propagation, we installed metallic reflecting walls next to the track. Thus, we obtain the signal interference characteristic from the real life tracking application in the longwall mining environment (cf. Fig. 4).

In Fig. 7 and 8, the trajectories of the BN on the motion test track for a complete motion cycle (A-B-A) are shown. Different configurations are compared to point out the influence of the redundant sensor information on the localization accuracy.

The trajectory for the CL algorithm using a binary LQnI

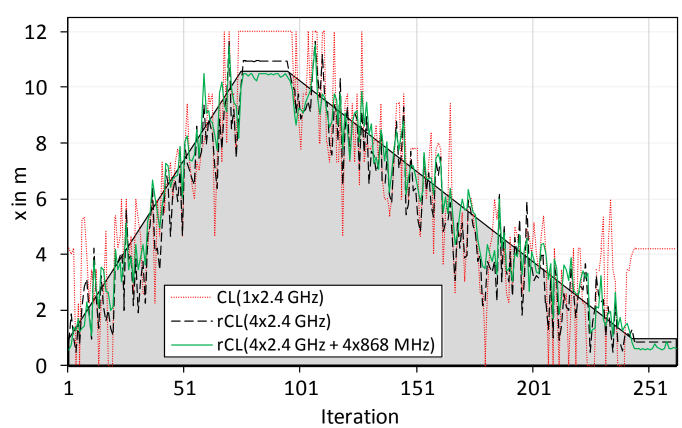

Fig. 7. Estimated trajectories for one-dimensional tracking measurements on a motion test track using range-free position estimation algorithms (CL – centroid localization with binary sensor input from a single RF channel, rCL – CL with LQnI information from redundant RF channels).

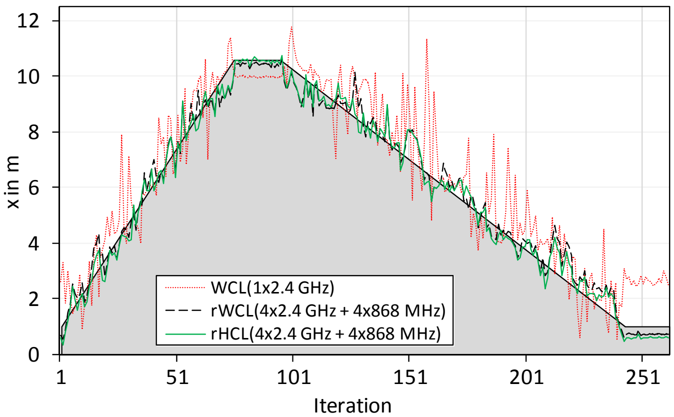

Fig. 8. Estimated trajectories for one-dimensional tracking measurements on a motion test track using range-based position estimation algorithms (WCL – weighted centroid localization with RSS sensor of a single RF channel, rWCL – WCL with RSS sensor information from redundant RF channels, rHCL – rWCL with additional weighting using the rCL approach with LQnI information from redundant RF channels).

information of a $2.4\,\mathrm{GHz}$ RF module shows large position errors. Using the rCL approach and four $2.4\,\mathrm{GHz}$ channels to calculate the LQnI (0..4), the position estimation error is reduced significantly. Another improvement is reached with rCL(8) which uses the radio link of additional four channels in the $868\,\mathrm{MHz}$ band.

A detailed comparison of the location estimation error (LEE) is given in Table I. The cumulative distribution functions (CDFs) of all presented centroid localization algorithms are shown in Fig. 9. The maximum error for rCL(8) is reduced by more than $50\,\%$ compared to the basic CL approach. The CDFs show that the range-free rCL(4) and rCL(8) approaches achieve even better results than the range-based WCL(1) setup without redundant RSS values. The rWCL(8) configuration using a weighting with a maximum of eight redundant RSS values shows a significant LEE reduction compared to WCL(1) and the range-free methods. The hybrid rHCL(8) configuration using eigth RSS for the distance approximation and additional LQnI information reaches the best results.

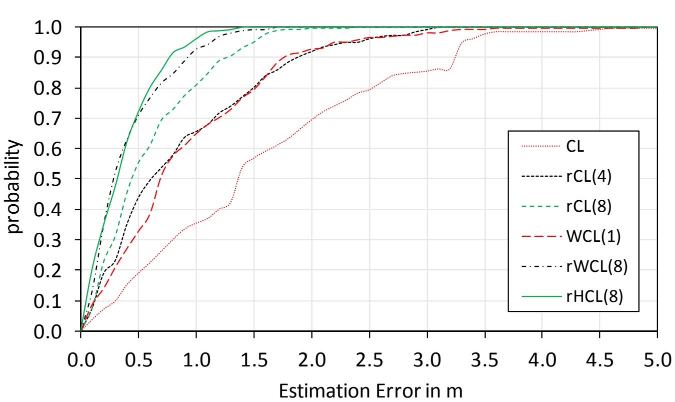

Fig. 9. Cumulative distribution functions for the location estimation error of a $9.6\,\mathrm{m}$ tracking measurement using RSS and LQnI information.

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT ESTIMATION TECHNIQUES (LEE - LOCATION ESTIMATION ERROR IN METERS)

	CL(1)	rCL(4)	rCL(8)	WCL(1)	rWCL(8)	rHCL(8)
LEE_{med}	1.40	0.61	0.44	0.68	0.30	0.31
σ_{LEE}	1.05	0.72	0.45	0.74	0.34	0.29
$LEE_{99\%}$	4.39	2.95	1.69	3.21	1.36	1.18
LEE_{max}	5.09	3.05	2.30	4.81	1.70	1.37

VI. Conclusions and Future Work

The comparison of the different range-free and range-based RF localization methods shows the importance of additional sensor information in fading environments. Adding redundancy to the distance approximations leads to a significant reduction of position estimation error. With the redundant RF channels, a localization approach using the available LQnI information is useful to correct some of the erroneous position estimates. The impact of the LQnI information on the distance and position estimation accuracy is evaluated by the RSS distribution of a real life localization with 20 reference nodes. With the proposed hybrid approach, a maximum LEE of $1.37\,\mathrm{m}$ is reached on a motion test track and thus, a good position estimation in multipath fading environments is possible with low infrastructural costs.

Further improvements of the hybrid approach focus on sophisticated diversity configurations with more than eight redundant RF channels and other carrier frequencies (e.g. $5\,\mathrm{GHz}$ ISM). For the RSS localization system a further development should comprise the replacement of the proprietary RF transceivers by standardized low-power protocols like ZigBee or Bluetooth low energy. Additional measurements in the real life application of underground longwall mining will provide a more detailed system benchmark, especially under the influence of the dust and heat conditions and the multipath propagation in the corresponding environment.

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