Received Signal Strength models for WLAN and BLE-based indoor positioning in multi-floor buildings

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Abstract—**This paper investigates the similarities and differences of the signal strength fluctuations and positioning accuracy in indoor scenarios for three types of wireless area networks: two Wireless Local Area Networks (WLANs) at 2.4 GHz and 5 GHz frequency, respectively, and one Wireless Personal Area Network (WPAN), namely the Bluetooth Low Energy (BLE). Two path-loss models based on weighted centroids and non-negative least squares estimation are presented: one including a floor loss factor, and the other one ignoring the floor losses, and the three signal types are compared in terms of the path-loss parameters, channel fluctuations and positioning accuracy, namely the distance errors and floor detection probabilities. The comparison is done based on real-field measurement data collected from a university building in Tampere, Finland. It is shown that all these three signal types have similar shadowing variances and close path-loss parameter values, and that a path-loss model considering floor losses gives the best floor detection probability, but not necessarily the smallest distance error.**

Keywords- Bluetooth Low Energy (BLE), Wireless Local Area Networks (WLAN); Wireless Personal Area Networks (WPAN), path-loss channel models, signal strength, shadowing.

I. INTRODUCTION AND STATE-OF-THE-ART

Wireless indoor positioning solutions based on Received Signal Strength (RSS) are becoming more widespread in the research and commercial worlds [4][5][7][8][9]. WLAN and Bluetooth signals are ubiquitous nowadays in indoor environments, thus making them ideal candidates for RSS-based indoor positioning. BLE beacons are currently attracting attention, because of the promise of long battery lives [10]. While indoor channel characteristics have been widely studied for WLAN 2.4 GHz-based positioning [5][6][7][9], there are only few studies so far about the RSS fluctuations for WLAN 5GHz [11] and BLE [12] signals. Moreover, comparisons between WLAN and BLE-based positioning in multi-floor buildings are hard to find in the current literature. In [12], a one-floor indoor study with less than 20 transmitters per system showed a better performance of BLE than WLAN 2.4 GHz and a lower shadowing variance for BLE than for WLAN. The multi-floor case has however not been investigated in [12], neither was the WLAN 5GHz included in the study.

It is the goal of this paper to shed a light on the similarities and differences of the RSS fluctuations and positioning accuracy via WLAN and BLE signals in multi-floor buildings, by employing measurement data in 2.4 and 5 GHz frequency bands. We will show that the BLE shadowing variance is, in our multi-floor environment, slightly higher than for WLAN 2.5 and 5GHz, and that the positioning performance in multi-floor buildings is rather similar for BLE and WLAN 2.4 GHz.

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II. MEASUREMENT CAMPAIGNS DESCRIPTION

All measurements have been conducted in a four-floor university building in Tampere, Finland, during August-December 2014. The measurement areas are shown in Table I. In the measurement campaign we used HERE indoor maps and proprietary software tools to register the measured RSS and the indoor position (i.e., "fingerprints"). At each change of direction, the position was entered manually on the map; in the rectilinear motion movements, the intermediate positions were obtained via linear interpolation. The measurement positioning errors were in the order of 0.5 m, due to possible slight inaccuracies in estimating visually the position on the map. The measurements were gridded by geometric averaging of measurements in each cell of a 1 m square horizontal grid on each floor. The building maximum measurement dimensions in x, y and z directions are shown in Table I.

A. *WLAN measurements*

The WLAN measurements were collected with a Nexus tablet containing a dual-frequency WLAN chipset (at 2.4 GHz and 5GHz frequency bands). The positions of the WLAN fingerprints on the map of the four-floor university are illustrated in Figure 1 after mapping the latitude-longitude map values into some local coordinates.

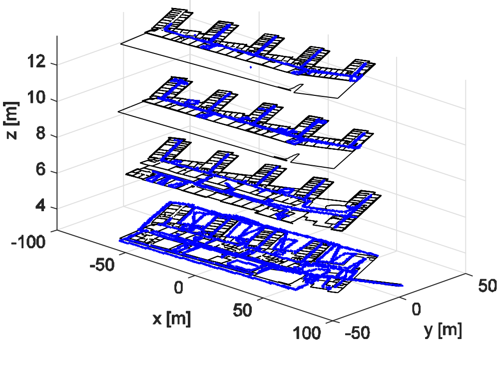

Figure 1. WLAN measurements in a 4-floor university building (the position of the fingerprints is shown in blue circles).

B. *BLE measurements*

The BLE transmitters were StickNFind (SNF) beacons transmitting at 2.4 GHz. The beacons were attached to walls and ceilings at various heights, 49 tags in the first floor, 23 in the second, and 6 in the upper floors. The distance between adjacent tags is about 8 m. The BLE measurements were collected with a Samsung Galaxy S5 mobile phone. The fingerprints' positions are shown in Figure 2.

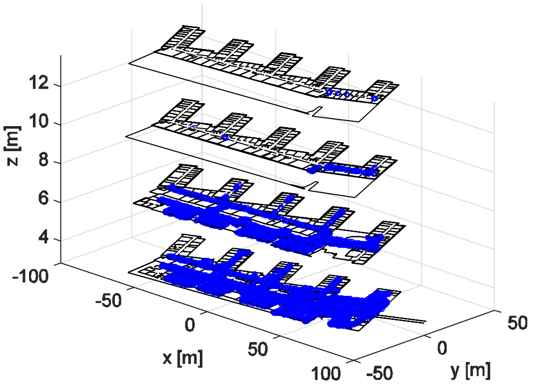

Figure 2. BLE measurements in a 4-floor university building (the position of the fingerprints is shown in blue circles).

C. *Measurements and building statistics*

The main characteristics of the measurement scenario are illustrated in Table I. We can see that the measurement areas in x-y directions slightly differ for the three signal types.

Also, as seen from Figure 2, the BLE measurements were mainly taken from the first and the second floor, as the tags were installed mostly at these floors. Thus, the tracks used in the position estimation were limited to these two floors for the BLE case. For BLE, the average and the maximum observed RSS were smaller than the WLAN average and maximum RSS, respectively. The number of transmitters seems much higher in WLAN 2.4 GHz case than in the BLE case, but, as it will be shown in Section IV TABLE II, the number of "independent" transmitters, meaning the transmitters located at different physical places from each other, is much smaller than the number of transmitters in WLAN cases. This is due to multiple Basic Service Set Identification (BSSID) support, when several MAC addresses can be allocated to the same WLAN physical location.

TABLE I - MEASUREMENTS ENVIRONMENT CHARACTERISTICS

	WLAN 2.4 GHz	WLAN 5 GHz	BLE 2.4 GHz
		Training phase	
Number of fingerprints after mapping into 1 m x 1m horiz. area	4417	2701	7650
Maximum measurement area in x- y directions [m × m]	176 × 77	164 × 77	135.27 × 63.60
Number of transmitters (counted as MAC addresses; several MAC addresses can occur at the same physical location in WLAN cases)	441	115	78
Number of fingerprints	4417	4417	7650
Minimum observed RSS in the training phase [dBm]	-94	-90	-106
Maximum observed RSS in the training phase [dBm]	-25	-30	-50
Kurtosis of all the observed RSS of all the transmitters	4.57	4.70	4.00
Skewness of all the observed RSS of all the transmitters	1.13	1.32	0.97
Average observed RSS per transmitter in the training phase [dBm]	-78.39	-75.10	-88.84
		Estimation phase	
Number of track points	3024	2302	1555
Floors at which the track points were taken (and percentages of the track points at those floors)	1 (35.6%)	1 (46.2%)	1 (70.7%)
	2 (33.3%)	2 (38.1%)	2 (29.3%)
	3 (17.9%)	3 (11.6%)	3 (0%)
	4 (12.1%)	4 (4.1%)	4 (0%)

III. PATH-LOSS CHANNEL MODELS

A Path-Loss (PL) model gives the relation between the RSS and the distance to the transmitter. When the transmitter location is not known, which is usually the case, the first step of the path-loss modeling is the transmitter location estimation. The next sub-sections explain the principles used in PL modeling.

A. *Transmitter location estimation*

The transmitter location is estimated based on the training data via a weighted centroid approach [1][2], in which the ξ -coordinate of each of the N_{tx} transmitters per system can be found via:

$$\xi_{ap} = \frac{\sum_{i=1}^{N_{heard_{ap}}} \xi_{i,ap} w_{i,ap}}{\sum_{i=1}^{N_{heard_{ap}}} w_{i,ap}}, \xi = x, y, \text{or } z, ap = 1,\ldots,N_{tx} \quad (1)$$

where $\xi_{i,ap}$ are the ξ - dimension (i.e., x, y or z) of the *i*-th fingerprint which heard the *ap*-th transmitter or access point, the $N_{heard_{ap}}$ is the number of points which heard the *ap*-th transmitter in the training phase, and $w_{i,ap}$ is a RSS-based weight associated to each fingerprint *i* and each transmitter *ap*. In our models, we used:

$$w_{i,ap} = 10^{\frac{P_{R_{i,ap}}}{10}} \quad (2)$$

where $P_{R_{i,ap}}$ is the RSS in decibels (dB) measured in the fingerprint *i* from the *ap*-th transmitter.

B. Path-loss modeling with floor losses (Model 1)

Once the transmitter location is estimated (or known), we model the RSS via a three-parameter-per –transmitter approach as follows:

$$P_{R_{i,ap}} = P_{T_{ap}} - 10 n_{ap} \log_{10}(d_{i,ap}) - 10 n_{ap} \log_{10}(f_{carr}) - F_{L_{ap}} N_{fl_{i,ap}} + \eta_{i,ap} \quad (3)$$
$$\text{with} \quad n_{ap} > 0, F_L > 0, P_{T_{ap}} < 0$$

where $P_{T_{ap}}$ is the apparent transmit power (in dB), n_{ap} is the path loss coefficient of the *ap*-th transmitter, f_{carr} is the carrier frequency in GHz, $F_{L_{ap}}$ is the floor loss factor of the *ap*-th transmitter (we assume constant floor loss per AP within the building), $d_{ap,i}$ is the distance between the *ap*-th transmitter and the *i*-th fingerprint, $N_{fl_{i,ap}}$ is the number of floors between the *ap*-th transmitter and the *i*-th fingerprint, and $\eta_{i,ap}$ is a noise factor, typically modeled as Gaussian, which models the shadowing fluctuations. $N_{fl_{i,ap}}$ and $d_{i,ap}$ are computed based on the estimated transmitter location (see eq. (1)). The proposed model is similar to the classical one-slope path-loss model [3][4][5][9], but with the following small differences: 1) it uses also the dependence on the carrier frequency, as in [6], in order to be able to compare better the path-loss parameters of the WLAN signals at different frequency bands, and 2) it uses a floor-loss parameter. The unknown vector is $\theta_{ap} = (P_{T_{ap}}, n_{ap}, F_{L_{ap}})^T$, and it can be estimated based on the training data, by solving the following *Non-Negative Least Squares (NNLS) problem*:

$$\begin{cases} H_{ap}\theta_{ap} = b_{ap} \\ diag([-1 \;\; 1 \;\; 1])\theta_{ap} \geq 0 \end{cases} \quad (4)$$

with

$$H_{ap} = \begin{bmatrix} 1 & -10\left(\log_{10}\left(d_{1,ap} f_{carr}\right)\right) & -N_{fl_{1,ap}} \\ 1 & -10\left(\log_{10}\left(d_{2,ap} f_{carr}\right)\right) & -N_{fl_{2,ap}} \\ \ldots & & \\ 1 & -10\left(\log_{10}\left(d_{N_{heard_{ap}},ap} f_{carr}\right)\right) & -N_{fl_{N_{heard_{ap}},ap}} \end{bmatrix},$$

and $b_{ap} = [P_{R_{1,ap}}, P_{R_{2,ap}}, \ldots., P_{R_{N_{heard_{ap}},ap}}]^T$.

C. Path-loss modeling without floor losses (Model 2)

The second considered PL model is the classical PL model without floor losses:

$$P_{R_{i,ap}} = P_{T_{ap}} - 10 n_{ap} \log_{10}(d_{i,ap}) - 10 n_{ap} \log_{10}(f_{carr}) + \eta_{i,ap} \quad (5)$$
$$\text{with} \quad n_{ap} > 0, P_{T_{ap}} < 0$$

The dependency on the carrier frequency was also kept for a fair comparison between the different signals and models considered here. Again, we can find the unknown parameter vector $\theta_{ap} = (P_{T_{ap}}, n_{ap})^T$ by solving a similar NNLS problem as in (4), where $F_{L_{ap}}$ was constrained to zero.

An example of the LS solutions in Model 1 (with floor-loss) and Model 2 (without floor loss) is shown in Figure 3 for an AP heard in more than 300 points. The fit in Model 1 depends on the floor of the fingerprints, thus offering a discontinuous curve. The estimation accuracy of each of these models is basically given by the shadowing standard deviation (std) in Table II.

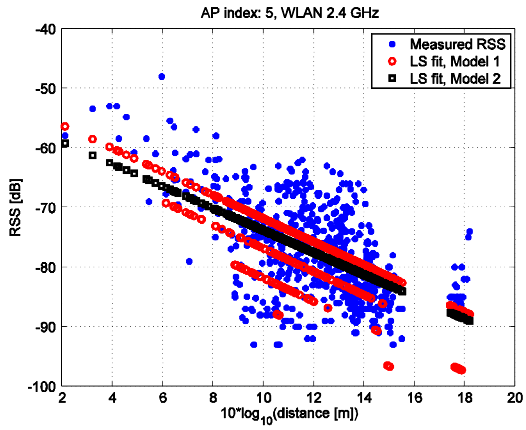

Figure 3. Example of the Least Squares fit for the two path-loss models.

IV. PATH LOSS CHANNEL STATISTICS

The three considered signals are compared according to their averaged path-loss parameters via the two PL models in TABLE II. Also the maximum distances at which a transmitter is heard and the number of independent transmitters (based on the estimated AP location) are shown. A transmitter is considered to be independent if it is placed at least 1 m away from all the other transmitters.

TABLE II - PATH-LOSS CHANNEL MODELS STATISTICS FOR THE CONSIDERED SIGNALS

		WLAN 2.4 GHz	**WLAN 5 GHz**	**BLE 2.4 GHz**
Maximum hearable distance, based on transmitter estimated position [m]		130.94	95.62	94.95
Number of "independent" transmitters (i.e., transmitters found at minimum 1 m apart from any other)		233	31	78
PL Model 1 (with floor loss) – average values	PT [dBm]	-46.35	-41.37	-70.39
	n [-]	1.69	1.78	1.32
	FL [dB]	4.93	3.62	5.91
	Shadowing std [dB]	5.56	4.84	5.85
PL Model 2 (without	PT [dBm]	-52.67	-45.42	-71.11
	n [-]	1.50	1.63	1.33

floor loss) – **av. values**	Shadowing std [dB]	5.92	5.32	6.15

We can see from TABLE II that WLAN signals at 2.4 GHz have the highest wall penetration, since they can be heard more than 30 m further away than the maximum heard distance for WLAN 5GHz and BLE. In BLE case, operating also at 2.4 GHz, this can be explained by a lower apparent transmit power of the APs, while in case of WLAN 5GHz, this is explained by the fact that signals at higher frequency are suffering higher path losses (see (3) and (5)). The shadowing standard deviation σ_{ap} is the standard deviation of the fitting error between the measurement data (blue dots in Figure 3) and the PL fits (red circles and black squares in Figure 3). TABLE II shows the average of σ_{ap}^2 for all estimated transmitters. If we compare WLAN 2.4 GHz with WLAN 5GHz in TABLE II, we can see that the average PL parameters and the shadowing standard deviation are rather close in values for both signal types. The BLE has a lower apparent transmit power, and a slightly lower path loss coefficient and a slightly higher shadowing standard deviation than WLAN signals.

V. POSITION ESTIMATION ALGORITHMS

There are mainly two approaches to estimate an RSS-based user position: 1) via fingerprinting [5][7] and 2) via probabilistic model approaches [5][8]. The fingerprinting requires the full training database information for all the N_{FP} fingerprints: $(x_i, y_i, z_i, P_{R_{i,ap}}), i=1,...,N_{FP}$, which can be rather high, while the probabilistic models rely on few parameters per AP (typically between 3 and 7), obtained during the training phase. We consider here two types of probabilistic approaches: the weighted centroid approach, which only uses the information about the estimated AP location and shadowing variance per AP: $(x_{ap}, y_{ap}, z_{ap}, \sigma_{ap}^2), ap=1,...,N_{tx}$, and the PL Model-based approaches, which uses the estimated AP location, the estimated PL parameters, and the shadowing variance: $(x_{ap}, y_{ap}, z_{ap}, \theta_{ap}, \sigma_{ap}^2), ap=1,...,N_{tx}$. For a fair comparison between these four position estimation algorithms, described in what follows, the same Gaussian likelihood function with estimated shadowing variance per AP.

A. *Fingerprinting (**FP**)*

In FP algorithm, the estimated user position is found by averaging over the position of N_{neig} "nearest" neighbours, where those "nearest" neighbours are obtained as the highest N_{neig} values of a likelihood function. The likelihood function in our case is the Gaussian likelihood $\mathcal{L}_i$:

$$\mathcal{L}_i = \exp\left(\kappa - \sum_{\substack{heard\\ap}} \frac{\left(O_{ap} - P_{R_{i,ap}}\right)^2}{2\sigma_{ap}^2}\right), i=1,..,N_{FP} \quad (6)$$

where O_{ap} is the RSS (in dB) of the *ap*-th transmitter observed by the mobile in the estimation phase, and $\kappa = \sum_{\substack{heard\\ap}} \log\left(\frac{1}{\sqrt{2\pi\sigma_{ap}^2}}\right)$.

B. *Weighted Centroid (**WeighCen**)*

The WeighCen approach estimates the user position as the weighted centroid of the positions of the heard transmitters, namely:

$$\xi = \frac{\sum_{\substack{heard\\ap}} \xi_{ap} u_{ap}}{\sum_{\substack{heard\\ap}} u_{ap}}, \xi = x, y, or\ z \quad (7)$$

where the weights are computed based on the observed RSS values: $u_{ap} = 10^{\frac{O_{ap}}{10}}$.

C. *Path-loss-based estimation*

In path-loss model estimation, the fingerprint location from the training phase is not transmitted to the mobile (reducing thus the amount of data to be transferred). Therefore, the estimation is based on a recreated likelihood grid. In our case, we used a 50 m × 50 m likelihood grid with 0.5 m step at each floor and this likelihood grid was centered around the WeighCen estimate at each step. The likelihood function becomes:

$$\mathcal{L}_i = \exp\left(\kappa - \sum_{\substack{heard\\ap}} \frac{\left(O_{ap} - \overline{P_{R_{i,ap}}}\right)^2}{2\sigma_{ap}^2}\right), i=1,..,N_{grid} \quad (8)$$

N_{grid} is the total number of grid points over all floors and $\overline{P_{R_{i,ap}}}$ is the re-created RSS based on a PL model, as seen in the next two sub-sections. In order to allow for some uncertainty in the model due to shadowing, the estimated user position found by averaging over the positions of all grid points which gives a likelihood value higher than $0.95\mathcal{L}_i$.

1) *With floor loss (**PL Model 1**)*

The recreated $\overline{P_{R_{i,ap}}}$ to be used in (8) is based on the estimated θ_{ap} from (4):

$$\overline{P_{R_{i,ap}}} = P_{T_{ap}} - 10 n_{ap} \log_{10}(d_{i,ap}) - 10 n_{ap} \log_{10}(f_{carr}) - F_{L_{ap}} N_{fl_{i,ap}} \quad (9)$$

*2) Without floor loss (**PL Model 2**)*

The recreated $\overline{P_{R_{i,ap}}}$ to be used in (8) is based on the estimated θ_{ap} from (4), where $F_{L_{ap}} = 0$:

$$\overline{P_{R_{i,ap}}} = P_{T_{ap}} - 10n_{ap}\log_{10}(d_{i,ap}) - 10n_{ap}\log_{10}(f_{carr}) \quad (10)$$

An example of the likelihood grid based on PL Model 1, together with all four estimates, is shown in Figure 4 for one transmitter of the WLAN 2.4 GHz signal.

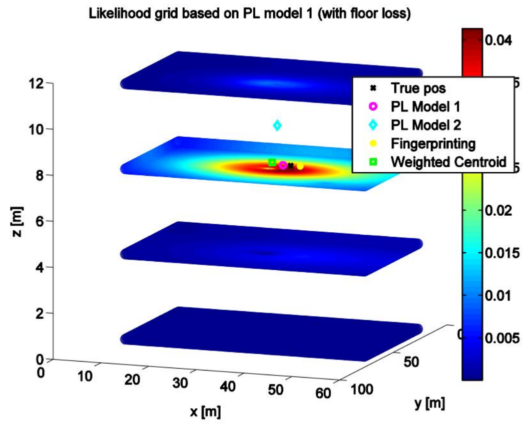

Figure 4. Example of a likelihood grid based o PL Model 1.

VI. POSITIONING RESULTS

The four position estimation algorithms have been applied to the three wireless area network signals and the results are presented in Figure 5 to Figure 7 and Table III. The training data has been different from the estimation data.

Figure 5, Figure 6 and Figure 7 show the Cumulative Distribution Functions (CDF) of the 3D-distance error e_{tr} between the estimated user position $\left(\hat{x}_{tr}, \hat{y}_{tr}, \hat{z}_{tr}\right)$ and the true user position $\left(x_{tr}, y_{tr}, z_{tr}\right)$ at *tr*-th track point:

$$e_{tr} = \sqrt{(x_{tr} - \hat{x}_{tr})^2 + (y_{tr} - \hat{y}_{tr})^2 + (z_{tr} - \hat{z}_{tr})^2} \quad (11)$$

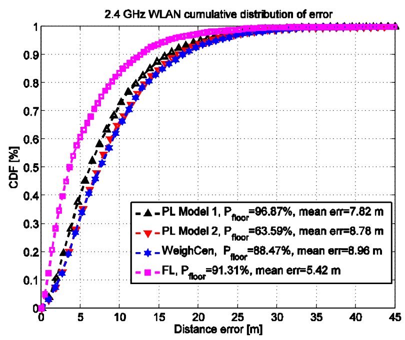

Figure 5. Distance error CDF based on WLAN 2.4 GHz signals.

Figure 5 is for WLAN 2.4 GHz, Figure 6 is for WLAN 5GHz and Figure 7 is for BLE. In all cases, we notice a clear advantage of using the floor-loss model (PL Model 1) compared to the PL model without floor loss (PL Model 2). The FP algorithm outperforms all the other probabilistic approaches in terms of distance error for WLAN situations, but probabilistic models seem slightly better than FP in BLE case. The weighted centroid approach works surprisingly well for all three signals in terms of achievable distance error, but typically such an approach is insufficient for achieving high floor detection probabilities, as seen in the figures' legends and also in Table III.

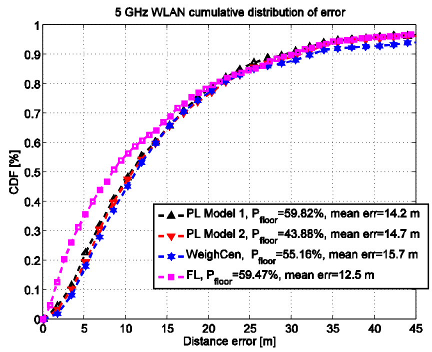

Figure 6. Distance error CDF based on WLAN 5 GHz signals.

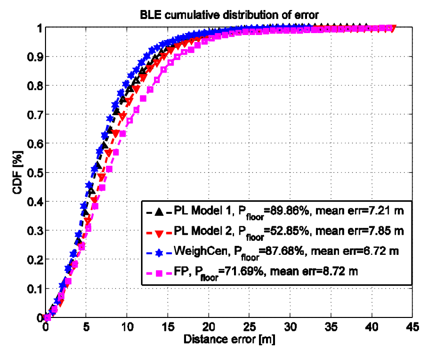

Figure 7. Distance error CDF based on BLE 2.4 GHz signals.

Table III presents further statistics of the positioning accuracy, namely the root mean square 3D distance error (computed over all the track points), the median 3D distance error, the floor detection probabilities, and the probability to obtain a 3D distance error less than 5 m. The mean values can be seen in the legends of Figure 5 to Figure 7. All these figures are based on one-shot estimates without any additional filtering; if past user trajectory is used, the distance error can be reduced to only few meters. In Table III, we showed in bold-faced letters the best value among all the four algorithms, for each signal. Clearly, a PL model with floor loses (PL Model 1) offers the best floor detection probability among all considered approaches. The minimum errors are however achieved either with FP (in WLAN case) or with the weighted centroid approach (in BLE case), pointing out to the fact that the position may be estimated close to the true x-y location, but one floor above or one floor below. The BLE and WLAN 2.4 GHz positioning performances are rather similar (with WLAN 2.4 GHz slightly better), which sheds a new light to the situation of multi floors, compared to what has been previously reported in the literature, e.g. in [12], where BLE shadowing variance was reported to be lower than for WLAN 2.4 GHz case, and the BLE performance based on a one-floor building study was reported to be better than for WLAN 2.4 GHz. The performance of WLAN 5 GHz is lower than for WLAN 2.4 GHz and BLE, mainly because we have much less transmitters operating at 5 GHz. Also, room level accuracy (e.g. 1-2 m accuracy) cannot be achieved without supplementary sensors and filtering stages.

TABLE III – STATISTICS OF PATH-LOSS CHANNEL MODELS

Signal	Algorithm	Root mean square 3D distance error [m]	Median 3D distance error [m]	Floor detection proba [%]	Proba of 3D distance error < 5 m [%]
WLAN 2.4GHz	FP	**7.6**	**5.4**	91.31	**60.8**
	WeighCen	11.1	9.0	88.47	26.9
	PL model 1	9.9	7.8	**96.87**	37.7
	PL model 2	10.8	8.8	63.59	27.8
WLAN 5 GHz	FP	**17.6**	**12.5**	59.46	**31.3**
	WeighCen	21.8	15.7	55.16	8.2
	PL model 1	19.2	14.2	**59.82**	11.5
	PL model 2	20.0	14.7	43.88	10.3
BLE	FP	10.5	7.5	71.69	24.4
	WeighCen	**8.5**	**5.8**	87.68	**38.5**
	PL model 1	8.7	6.1	**89.86**	36.3
	PL model 2	9.3	7.0	52.85	24.7

VII. ALGORITHMS COMPLEXITY

Table IV shows the necessary number of parameters to be stored from the training phase and transferred to the mobile in the estimation phase in each of the four considered algorithms and for all the analyzed measurement data. One could state that this number of parameters is directly proportional with the algorithm complexity, because it is directly related with the amount of data transfer to the mobile.

TABLE IV – NUMBER OF PARAMETERS TO BE STORED PER BUILDING

Algorithm	WLAN 2.4 GHz	WLAN 5 GHz	BLE 2.4 GHz
WeighCen	1764	460	312
PL model 1	3087	805	546
PL model 2	2646	690	468
FP	139302	22525	41715

Clearly, in our considered building, the probabilistic approaches can reduce the necessary database between 28 and 133 times, which shows a huge complexity gain if probabilistic approaches are used instead of FP, a fact also reported in [5].

VIII. CONCLUSIONS

In this paper, the similarities and differences between WLAN and BLE signals operating at 2.4 and 5GHz have been investigated, in terms of path-loss modeling and RSS-based positioning accuracy. Two PL models based on the distance to transmitter and carrier frequency have been presented; one included a floor-loss parameter, and the other one assumed omnidirectional signal propagation. It can be seen that a PL model with a floor-loss parameter can improve significantly the floor detection probability, but that the 3D distance error is not necessarily better than with the other considered algorithms. It was also shown that a low distance error can be obtained in both WLAN and BLE cases with a very simple weighted centroid approach, but that such approach is insufficient for high accuracy in the floor detection. The general conclusion is that the WLAN and WPAN signal propagation in multi-floor buildings is very similar, and that a PL a model with a floor-loss factor can be successfully employed for all these signals in order to achieve good floor detection probabilities and low position estimation errors.

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