Indoor localization via WLAN path-loss models and Dempster-Shafer combining

Parinaz Kasebzadeh
Tampere University of Technology
Tampere, Finland
Email:parinaz.kasebzadeh@student.tut.fi

Gonzalo-Seco Granados
Universitat Autonoma de Barcelona
Bellaterra, Spain
Email:gonzalo.seco@uab.es

Elena Simona Lohan
Tampere University of Technology
Tampere, Finland
Email:elena-simona.lohan@tut.fi

***Abstract*—In this paper, in order to improve the accuracy of mobile user location estimation, we investigate a new approach based on path-loss algorithms with non-Bayesian data fusion based on Dempster-Shafer Theory (DST). Traditionally, Bayesian framework is used in Wireless Local Area Network (WLAN) positioning. Nevertheless, alternative approaches such as DST have also good potential in WLAN positioning, as it has been previously shown by using DST with WLAN fingerprinting. Our paper focuses on Path-Loss (PL) probabilistic approaches, which have the advantage of a lower number of parameters and lower implementation complexity compared with the fingerprinting approaches. We combine, for the first time in the literature, the PL position estimators with DST. PL approaches can be implemented with a variety of algorithms, and the deconvolution algorithms used in our paper are among the most promising implementations, due to their simplicity. We study the performance of the PL approaches with real-field data measurements and we show that the DST can increase the floor detection probability and decrease the distance Root Mean Square Error (RMSE) compared to the approaches using Bayesian combining.**

***Index Terms*—Indoor WLAN localization, Dempster Shafer data fusion, deconvolution approaches, unknown Access Points location, Received Signal Strength (RSS), path-loss models.**

I. MOTIVATION AND STATE OF ART

The Wireless Local Area Network (WLAN)-based indoor localization is one of the most studied techniques for indoor localization field nowadays. Accurate user's locations and real-time location estimations in indoor environments are important goals to achieve reliable Location Based Services (LBSs). Consequently, there is a growing interest in developing effective positioning and tracking systems. Although GNSS systems are widely spread for outdoor positioning, their performance is not satisfactory in indoor environment due to limited availability of the Line-Of-Sight (LOS) from GNSS satellites, due to low Carrier-to-Noise ratios of the satellite signals in indoor environments, and due to multipath propagation [8]. Hence, the GNSS system has limited indoors usage and this makes appealing the alternative techniques, such as WLAN-based positioning [9], [10], [11], cellular-based positioning [13], Bluetooth-based positioning [7] or ZigBee-based positioning [12]. Among these alternative techniques, WLAN -based localization using Received Signal Strength (RSS) information is one of the most studied and promising techniques for large-scale indoor positioning and it is the purpose of our paper.

The Gaussian framework and the Bayesian data fusion are usually the default choices to address the indoor positioning, due to their ease of being understood and modeled. Bayesian theory typically minimizes the probability of a wrong classification. However, it has some limitations such as, the difficulty for expressing the conditional probabilities, and inconvenience of obtaining the prior probabilities needed in Bayesian combining. Moreover, Bayesian theory cannot deal well with uncertain states or with incomplete or incorrect data measurements [2], [15]. These limitations triggered the interest for investigating alternative non-Bayesian theories. One of such non-Bayesian frameworks is the Dempster-Shafer Theory (DST). In Dempster-Shafer evidence theory, the received signal strengths from multiple access points can be fused with different beliefs or underlying uncertainties and such theory allows for inherent errors in measurement data and for incomplete information. Dempster-Shafer theory is based on the non-classical idea of "mass" as opposed to probability. DST has been previously studied in the context of WLAN positioning in [4] and [14]. In both these studies, only the fingerprinting approaches have been addressed. However, for making the WLAN localization more suitable for mobile computing, probabilistic path-loss models can be used instead of the fingerprinting [10],[1]. In this paper, we combine for the first time in the research literature (to the best of the Author's knowledge) the path-loss-based WLAN estimation with the Dempster-Shafer evidence theory and we analyze the resulting approach with WLAN measurement data from several multi-floor buildings. We also compare the DST estimates with the Bayesian estimates. We remark that parts of this study have also been analyzed in the master thesis of the first Author [15] and that the underlying theory of how to apply DST to WLAN-based positioning in multi-floor buildings has been introduced in [14].

The rest of the paper is organized as follows: in Section II, the traditional RSS-based path-loss modeling with classical Bayesian approaches are reviewed. Section III presents the basic concepts about DST and then it explains the RSS-based path-loss algorithm with DST approach used for the data fusion part (meaning the combination of information coming from different Access Points heard in the building where the

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indoor positioning is desired). Section IV gives the comparison results between the traditional Bayesian approach and the new DST approach, based on the real-field datasets, collected via extensive measurement campaigns in several types of buildings in Tampere city, Finland. Finally, conclusions are given in the last section.

II. PATH LOSS MODELING AND RSS-BASED LOCALIZATION

Path-Loss (PL) models are alternative estimation models to fingerprinting which can decrease substantially the database sizes and the storage space needed to do the mobile-based positioning [1]. The path-loss positioning approaches have been examined in different studies [5], [10], [1]. For example, Nurminen et al. in [5] used an iterative Gauss Newton method to cope with the non-linearities in the PL model. The path-loss approach used in [10] was based on linear regression and trilateration. The approach in [1] is the one adopted in here and it uses various deconvolution approaches, such as the Least Squares (LS), the Weighted Least Squares (WLS) and the Minimum Mean Square Estimators (MMSE) to estimate the part loss parameters per Access Point (AP). The AP location is also based on the deconvolution estimators, using an iterative approach. The difference between our paper and [1] is that the data fusion of the information coming from all heard APs is done via DST in here (while Bayesian combining was used in [1]). We show that the result with non-Bayesian framework can outperform the results based on Bayesian data fusion. The reason for selecting the deconvolution approaches instead of Gauss Newton methods is their lower complexity of implementation. Nevertheless, the DST method described in here can be employed with other path-loss estimators as well and it is not restricted to the deconvolution approaches.

Similarly with any other RSS-based localization solutions, the path-loss estimators have two phases for location determination: The training phase and the estimation phase.

After capturing the training data with dedicated measurement tools and in an offline phase, a fingerprints dataset is created, which consists of RSS values and the position of each fingerprint point. In our measurement campaign, the data was collected manually, using a Windows Acer tablet with dedicated (proprietary) software. The building floor maps were available during the data collection, but the AP location was unknown. The AP location was estimated base on the following weighted-centroid formula [16], [17], which is a slight modification from [1] where an iterative approach has been used. Indeed, our tests showed that the weighted centroid formula gives similar results with the iterative approach described in [1] and it has lower computational complexity:

$$\mathrm{X_{ap}} = \frac{\sum \mathrm{w_{i,ap}X_i}}{\sum \mathrm{w_{i,ap}}}, \quad \mathrm{Y_{ap}} = \frac{\sum \mathrm{w_{i,ap}Y_i}}{\sum \mathrm{w_{i,ap}}}, \quad \mathrm{Z_{ap}} = \frac{\sum \mathrm{w_{i,ap}Z_i}}{\sum \mathrm{w_{i,ap}}}, \tag{1}$$

where (X_i, Y_i, Z_i) are the 3D coordinates of the i-th fingerprint that heard *ap*-th access point and $w_{i,ap}$ is RSS value between the *ap*-th access point and *i*-th grid point.

The traditional path-loss modeling has been used, as illustrated below:

$$\mathrm{P_{i,ap}} = \mathrm{P_{T_{i,ap}}} - 10\mathrm{n_{ap}}\log_{10}\mathrm{d_{i,ap}} + \eta_{\mathrm{i,ap}}, \tag{2}$$

where $P_{T_{i,ap}}$ and n_{ap} are apparent transmit power and the path loss coefficient characterizing the *ap*-th access point. In [1], four different path loss models were analyzed (the traditional one, the traditional one with a floor loss factor, the two-slope path loss model and the two-slope path loss with floor attenuation factor) and it was shown that the traditional model from (2) offers the best trade-off between complexity and performance. This is the reason for choosing this one-slope path loss model in here.

Further on, in the training phase based on measured RSS, the AP positions and AP parameters $P_{T_{i,ap}}$ and n_{ap} are estimated by using deconvolution estimator formulas presented in [1]. In other words, in the training phase we estimate the path loss coefficient $\hat{n}_{ap}$ and the apparent transmit power $\hat{P}_{T_{i,ap}}$ for each AP.

Then, in the estimation phase, we only transmit to the mobile the set of the estimated parameters ($\hat{P}_{T_{i,ap}}$,$\hat{n}_{ap}$) for all the AP in a building. The mobile builds locally a grid with uniform spacing between the ggrid points (e.g., 1 m). Considering this re-created grid around the MS, the RSS in each grid point is estimated using the set of parameters ($\hat{P}_{T_{i,ap}}$,$\hat{n}_{ap}$). Now a RSS dataset is ready and estimating the MS location is next step. In the traditional Bayesian estimation, this is done by maximizing the joint likelihood function from all heard APs, where an individual likelihood per *ap* AP and *gp* recreated grid point is computed as:

$$\mathrm{p_{ap,gp}} = -\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)\exp\left(-\frac{(\mathrm{P_{ap}} - \hat{\mathrm{P}}_{\mathrm{ap,gp}})^2}{2\sigma^2}\right), \tag{3}$$

where P_{ap} is the RSS value heard by the mobile from the *ap*-th AP, $\hat{P}_{ap,gp} = \hat{P}_{T_{i,ap}} - 10\hat{n}_{ap}log_{10}d_{i,ap}$ and σ is an estimate of the shadowing standard deviation in the building. In our studies we took it equal to 6 dB in logarithmic scale, based on findings from [18], [19] (i.e., $\sigma^2 = 15.85$). The joint likelihood per grid points becomes:

$$\mathrm{p_{gp}} = \sum_{\mathrm{heardAPs}} \mathrm{p_{ap,gp}}, \tag{4}$$

and the mobile position is estimated in the grid point $\widehat{gp}$ which maximizes p_{gp}:

$$\widehat{\mathrm{gp}} = \mathrm{argmax_{gp}}(\mathrm{p_{gp}}). \tag{5}$$

The major difference between [1] and our approach is in estimation phase. In the estimation phase from [1], the position of MS will be estimated by computing the Gaussian likelihoods per heard AP, then summing them for all heard APs. In our estimation phase, we will apply the Dempster-Shafer (DS) combination rules derived in [14], as explained in the next section, in order to merge the information coming from various APs (instead of simply summing the likelihoods as in the Bayesian approach). Instead of working with probabilities, we work with the so-called concept of masses [2], [3], [4] and we use three types of 'masses' to each grid point: $m_{gp}(I)$, $m_{gp}(N)$ and $m_{gp}(I, N)$. $m_{gp}(I)$ represents the probability that the user is "In this position" (meaning in that particular grid point gp; $m_{gp}((N)$ shows the probability that the user is "Not this position"; $m_{gp}((I, N)$ shows the uncertainty about evidence and has the meaning that the MS can be or not in that position. All our computation based on DST implementation are illustrated in the next section.

III. DEMPSTER SHAFER MODELING

Dempster-Shafer (DS) is a mathematical theory of evidence and plausibility reasoning. The main feature of DST is the combination of evidence obtained from multiple sources by modeling the conflict between evidences. The DS works with masses instead of probabilities. Image processing, signal detection, target identification, multiple-attribute decision making, location detection and other intelligent systems are the fields where the DST provides an effective way to solve various problems. DST has been applied in the context of WLAN positioning in only two papers, to the best of the Authors' knowledge [4], [14] and both of them focused on fingerprinting approaches. In here, we use DST model in the context of PL approaches described in previous Section.

A. Dempster-Shafer Theory

The Dempster-Shafer theory's main functions are: Belief function (Bel), Plausibility function (Pl), Basic probability assignment function (bpa) and mass function (m). In the DS theory, all possible mutually exclusive context facts of the same kind will be in "the frame of discernment" which is denoted by θ. The frame of discernment, θ, consists of all hypotheses which the information sources can provide evidence. This set is finite and consists of mutually exclusive propositions that span the hypotheses space. The size of the frame of discernment is 2^n where *n* is number of events. The mass function (m) is a fundamental part of the evidence theory. It sets to the interval between 0 and 1. The mass function will be equal to 0 when set is null, and the mass functions summation of all the subsets of the power set is 1. This is mathematically expressed as:

$$\mathrm{m} : 2^{\theta} \rightarrow [0, 1], \tag{6}$$

where set 2^{θ} of all possible combination within the frame of discernment, including the empty set.

$m(A)$ means the value of the mass function for a given set A. The value of $m(A)$ is only related to the set A, and does not related to subsets of A. The mass function has the following properties:

$$\mathrm{m}(\emptyset) = 0, \qquad \sum_{A \subseteq \theta} \mathrm{m}(\mathrm{A}) = 1, \tag{7}$$

The belief function and the plausibility function are defined based on the lower and upper band of bpa interval.

$$[\mathrm{Belief(A)}, \mathrm{Plausibility(A)}], \tag{8}$$

The belief function is the function that accounts for all the evidence B that supports the given hypothesis A. On the other hand, lower band belief for a hypothesis A is calculated by the bpa summation of the evidence B of the set of interest hypothesis A. The belief function illustrates the lower probability limit. It is expressed as equation:

$$\mathrm{Bel(A)} = \sum_{B | B \subseteq A} \mathrm{m(B)}, \tag{9}$$

The plausibility function accounts for all the observations that do not rule out the hypothesis A. The plausibility function presents the upper probability limit. In addition, the upper band belief for a hypothesis A is calculated by the bpa summation of the evidence B that intersect the set of the hypothesis A. It is illustrated as (10)

$$\mathrm{Pls(A)} = 1 - \sum_{B \cap A = \emptyset} \mathrm{m(B)}, \mathrm{A} \in 2^{\theta}, \tag{10}$$

Neither plausibility nor belief are additive measures. This means that the summation of all beliefs or plausibility is not mandatory to be equal to 1 [3].

Furthermore, the plausibility function can also be derived from the belief function; it is illustrated by (11)

$$\mathrm{Pls(A)} = 1 - \mathrm{Bel}(\bar{\mathrm{A}}), \tag{11}$$

where $\bar{A}$ is the complement of A. By defining plausibility in term of the belief come from the fact that is all basic assignments must sum to 1.

One way to make the analysis more cost-effective is using the belief entropy or the core entropy. That is because this way different features of information content in mass distribution, (6) are utilized. Dissonance measures and confusion measures which represent the uncertainty in mass distribution are expressed by following formulas:

$$\mathrm{E(m)} = -\sum_{\mathrm{A} \in 2^{\theta}} \mathrm{m(A)} \log_2 \mathrm{Pls(A)}, \tag{12}$$

$$\mathrm{C(m)} = -\sum_{\mathrm{A} \in 2^{\theta}} \mathrm{m(A)} \log_2 \mathrm{Bel(A)}, \tag{13}$$

where Pls(A), Bel(A) are as defined in (10) and (9), respectively. $E(m)$ and $C(m)$ represent also measure of dissonance and measure of confusion, respectively. They display the uncertainty in a mass distribution. The key step in DST is the rule of combining the evidences coming from different sources (in this case, the APs). The state of each event will be updated based on the Dempster combination rules formula, described in Section III.B.

In the next section, we first formulate the WLAN localization problem in terms of masses, and then we explain how the DST can be applied to this problem. We have defined the masses and combining rules in two different ways in term of estimating the mobile user location with minimizing the distance error. One of them is based on what introduced in [4], and we have named it "Zhang" through this paper. The other one is introduced in [14] by making some modification on Zhang approach. Both are used now in the context of PL estimation (instead of fingerprinting).

B. Data fusion for WLAN-based location estimation based on the DST

Three different possibilities of MS position that are considered in our work are extensions of the approach presented in Zhang [4]. They are: MS presence in grid point shown by *I*, MS presence in not grid point shown by *N*, and MS position is uncertain that is shown by *(*I, N). To rephrase these three possibilities, we can see the situation as having two states: uncertain or certain, and the certian state has further two subcases: either the MS is in that grid point: I, or it is not: N. Now, if we assume that a probability $a \leq 1$ allocated to state (I, N), it means that the probability of the 'certain' state $1-(I, N)$ is $1-a$. In certain state, the state I happens with probability p and state N is with probability $1-p$. The masses allocated to all 3 possible states *I, N ,(I, N)* can be set as follows [14]:

$$\begin{aligned} \mathrm{m(I)} &= (1-a)p, \\ \mathrm{m(N)} &= (1-a)(1-p), \\ \mathrm{m(I,N)} &= a \end{aligned} \tag{14}$$

The above equations can be computed per grid point *gp* and per AP *ap* [14].

The uncertainty factor a associated with each AP, a_{ap}, in the building is an important issue that should be considered after the masses are defined. The authors in [4] (i.e., Zhang approach), defined the uncertainty factor as fraction of the heard power by an AP, as in (15). It means that the higher the heard power is, the higher uncertainty we associate to that particular AP, which is in fact counter-intuitive, as already emphasized in [14]:

$$\mathrm{a_{ap|Zhang}} = \frac{10^{\frac{\mathrm{RSS_{ap,MS}}}{10}}}{\sum_{\mathrm{all\ heard\ ap}} 10^{\frac{\mathrm{RSS_{ap,MS}}}{10}}}, \tag{15}$$

where $RSS_{ap,MS}$ is the RSS (in dB scale) heard at the MS from the access point *ap*. Our studies showed that Zhang definition of the factor $a_{ap|Zhang}$ gives very poor results both for fingerprinting approaches [14] and for PL approaches (as shown in the next section). Therefore, we will use instead the uncertainty factor defined in [14]:

$$\mathrm{a_{ap|proposed}} = 1 - \frac{10^{\frac{\mathrm{RSS_{ap,MS}}}{10}}}{\sum_{\mathrm{all\ heard\ ap}} 10^{\frac{\mathrm{RSS_{ap,MS}}}{10}}}. \tag{16}$$

At this step, there are again two possibilities:

1) we can use only the commonly heard access points (*ap*) between the MS and the considered *gp*;
2) we can use all heard access points, either by the MS or by the *gp*, by setting the non-heard RSSs to a sufficiently small value (the not-heard RSS for example, if *ap* is heard by MS but not by the *gp* , take $RSS_{ap,gp} = -100$ (dB)).

We tested both approaches and we noticed that the first approach is slightly better, thus it will be used in what follows.

The DS combining rule between two heard access points 1 and 2 is given by the following equation [3], [4], [14]:

$$\mathrm{m_{12}(C)} = \frac{\sum_{\mathrm{A\cap B=C}} \mathrm{m_1(A)m_2(B)}}{1-\mathrm{K}}, \tag{17}$$

The main idea behind (17) is that the joint mass maximizes the evidence which supports the same conclusion, while minimizing the contradictory evidence. where $C \neq \emptyset$ and K is calculated by (18).

$$\mathrm{K} = \sum_{A,B|B\cap A=C} \mathrm{m_1(A)m_2(B)}, \tag{18}$$

where K is mass function associated to the conflict among sources. $1-K$ is a normalization factor in the DS combination rule formula. This normalization factor could have some effect on completely ignoring conflict. The way that we define the normalization factor affects the result that we get from the DS combination rule because of its influence on conflict. There are different ways to determine normalization factor. The definition of $m_{12}(I)$, $m_{12}(N)$ and $m_{12}(I, N)$ were shown in [14]. They are translation of (17) for $C = I$, $C = N$ and $C = \{I, N\}$. We have used those formulas for this research. In addition, a detailed explanation about how to extend (iteratively) the calculation from (17) when there are more than 2 heard Access Points is also given in [14].

Mobile user location estimation is done by computing the masses for each grid point and applying iteratively the above rule for all heard access points. Our tests also showed that the order of combining different heard APs is not important. In our simulation, we used a combining order from the strongest heard AP to the weakest heard AP. The estimated position is determined according by maximizing the belief or mass (I):

$$\mathrm{max_i}\left(\mathrm{Bel_i(I)}\right) = \mathrm{max_i(m_i(I))}, \tag{19}$$

In the next section the results are shown and compared with each other.

IV. RESULTS WITH REAL-FIELD DATA

The DS combining rule described in previous section was implemented with real-field data gathered from three different building in Tampere city, Finland: a university building, an office building and a Mall. For measurements, we used an Acer Windows tablet with incorporated WLAN receiver and its associated (proprietary) software. We manually set the user positions when doing the measurements, based on available maps and users' visual estimates about where she or he is positioned on the map. No sensors were available on the tablet at the time when doing the measurements (during years 2011−2012).

In the followings, we illustrate the results of our implementation based on Path-loss models and Bayesian versus DST models. DST is shown for 2 different parameters: our approach and Zhang's approach. The exact location of mobile user was stored for obtaining the statistics.

The main parameters for comparing these two different methods are Root Mean Square Error (RMSE) and the probability of correct floor detection (P_d), similarly with [14], [15]. The RMSE of the distance error was computed via:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{error_i})^2}, \qquad (20)$$

where N is the number of estimated user track points, and $error_i$ is the error distance computed as

$$\mathrm{error_i} = \sqrt{(\mathrm{X_{t,i}} - \mathrm{X_{e,i}})^2 - (\mathrm{Y_{t,i}} - \mathrm{Y_{e,i}})^2 - (\mathrm{Z_{t,i}} - \mathrm{Z_{e,i}})^2}, \quad (21)$$

and $(X_{t,i}, Y_{t,i}, Z_{t,i})$ are the true 3D coordinates of user track point i, while $(X_{e,i}, Y_{e,i}, Z_{e,i})$ are its estimated 3D coordinates.

The floor detection probability P_d is calculated as:

$$\mathrm{P_d} = \frac{\text{Number of correct floor estimates}}{\text{Number of total estimates}}. \qquad (22)$$

Figure 1 shows the RMSE and P_d values for three different methods (Bayesian, DST with our parameter a_{ap} and DST with Zhang's approach) in an university building based on 11 different tracks. The fluctuations are track dependent and are normal because the tracks were picked randomly within the buildings.

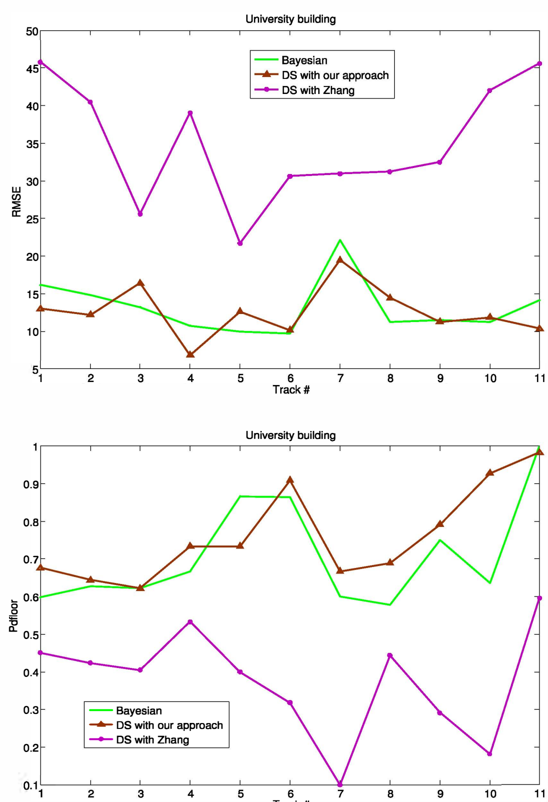

Fig. 1: RMSE and P_d floor illustration in a University building .

Although the DST approach based on our combining does not have the best results (compared with the Bayesian combining) in all the tracks, in most tracks, it outperforms the Bayesian -based combining. Especially if we focus on the floor detection probability, DST performance is visibly better than the Bayesian except in one track among the studied ones (track 5). Table I also shows the numerical results plotted in 1.

TABLE I: Path-Loss model with Bayesian and DST for an university building.

University 4-floor building	PL + Bayesian		PL + DST, our approach (a_{ap} from eq. (16))		PL+ Zhang (a_{ap} from eq. (15)	
	Pd%	**RMSE (m)**	**Pd%**	**RMSE (m)**	**Pd%**	**RMSE (m)**
track 1	59.80	16.14	67.65	13	45.10	45.79
track 2	62.71	14.80	65.25	12.15	42.37	15.07
track 3	62.16	13.23	59.46	16.41	40.54	25.58
track 4	66.67	10.77	73.33	7.25	53.33	39.04
track 5	86.67	9.94	73.33	12.63	40	21.67
track 6	86.36	9.68	90.91	10.15	31.82	30.61
track 7	60	22.15	66.67	19.47	10	30.97
track 8	57.78	11.23	68.89	14.44	44.44	31.23
track 9	75	11.47	79.17	11.28	29.17	32.49
track 10	63.64	11.27	92.73	11.87	18.18	42.03
track 11	100	14.15	98.25	10.37	59.65	45.60
Average	70.98	13.16	**75.96**	**12.63**	37.69	32.73

The results obtained for Bayesian PL estimates are similar with those reported in [1] and the rather low floor detection probability in some of the studied tracks is normal for PL approaches, which are not able to capture the floor dynamics as well as fingerprinting approaches. We emphasize however the fact that PL approaches have significant lower complexity than fingerprinting approaches (it was shown for example in [1] that the database size can be reduced even 10 times when PL approaches are used instead of fingerprinting, and thus the transfer from the location server database to the mobile is much faster and requires less data rate and less battery consumption).

Based on the results shown in here, we can see that on average, our DST implementation with PL outperforms both the Bayesian implementation and the DST implementation of Zhang. Clearly, Zhang's choice of parameters is suboptimal, as seen from the large RMSE and low P_d values from Table I. The same observations were made also when using fingerprinting estimators instead of path-loss estimators in [14].

Table II shows the performance of the three studied algorithms in a seven-floor office building. The performance of the path-loss model with DS approaches based on our combining outperforms other approaches in all studied cases.

TABLE II: Path-Loss model with Bayesian and DST for an office building.

Office 7-floor building	PL + Bayesian		PL + DST, our approach (a_{ap} from eq. (16))		PL+Zhang (a_{ap} from eq. (15)	
	Pd%	**RMSE (m)**	**Pd%**	**RMSE (m)**	**Pd%**	**RMSE (m)**
track 1	69.05	4.24	83.33	4.19	16.67	11.41
track 2	48.57	6.28	91.43	5.24	20	13.35
track 3	56.06	6.47	84.85	5.45	16.67	20.49
AVERAGE	57.89	5.66	**86.53**	**4.96**	17.78	15.08

Table III shows also the results in a six-floor shopping mall. In here. floor detection is clearly the best with our

DST implementation. It was noticed before in [1], that floor detection is the most difficult problem in indoor positioning inside multi-floor buildings. Especially in Malls with many open spaces, it is problematic to correctly detect the right floor. According our results, DST is able to improve the floor detection probabilities, despite the fact that the distance RMSE error remains comparable (or slightly worse) with the Bayesian approach.

TABLE III: Path-Loss model with Bayesian and DST for a shopping center

Shopping mall, 6-floor building	**PL + Bayesian**		**PL + DST, our approach (a_{ap} from eq. (16))**		**PL+ Zhang (a_{ap} from eq. (15)**	
	Pd%	**RMSE (m)**	**Pd %**	**RMSE (m)**	**Pd%**	**RMSE (m)**
track 1	100	14.96	93.75	17.24	62.50	53.67
track 2	100	13.09	100	11.80	100	47.16
track 3	23.08	21.65	30.77	38.42	23.08	29.65
track 4	40	21.50	75	21.76	50	38.68
track 5	46.15	21.82	46.15	27.90	7.69	28.90
track 6	40	26	66.67	30.55	0	34.62
track 7	51.85	14.50	66.67	13.62	5.56	34.24
track 8	66.67	19.44	50	18.55	16.67	40.15
track 9	58.12	19.12	76.07	20.02	14.53	45
AVERAGE	64.92	**19.12**	**67.23**	22.20	31.11	39.11

The Cumulative Density Function (CDF) of the distance error $error_i$ was also investigated, according to (23):

$$\mathrm{CDF}(\beta) = \mathrm{Probability}(\mathrm{error_i} \leq \beta), \tag{23}$$

The results are shown in Figure 2, for the university building (similar plots were obtained for the other two studied buildings).

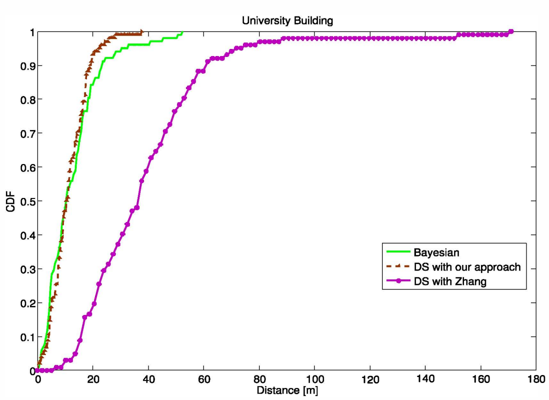

Fig. 2: Example of the Cumulative Distribution Function (CDF) of absolute distance error for a university building .

V. CONCLUSIONS

In this paper, we investigated the use of DST theory with probabilistic path-loss approaches for WiFi-based indoor positioning. The path-loss parameter estimation was based on deconvolution approaches. The results show that DST combining has non-negligible potential for improving floor detection probabilities, compared to the traditional Bayesian approaches. Although the results are not always better with DST (compared with the Bayesian combining), they seem very promising in environments with measurement data errors or incomplete data. However, there is still place for optimization of the DST parameters.

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