Performance Analysis of some Fingerprinting Based Localization Techniques Using UWB Signaling

Aawatif Hayar, Hicham Anouar and Bassem Zayen
Institut Eurecom B.P. 193, 06904 Sophia-Antipolis Cedex - France
Email: {hayar, anouar, zayen}@eurecom.fr

***Abstract*— In this paper[1], we give an analysis of the performances of two fingerprinting-based localization schemes using IR-UWB signaling. The first scheme uses channel's power delay profile as fingerprints and least square error as matching function. The second one use channel 2nd. order statistics as fingerprints and maximum likelihood estimation as matching function. The analysis allows us to model some key parameters as the grid dimensions and the number of samples in building the database, which help in selecting optimal setup of the localization system offline. The performances limitations are given in term of upper bound on the mean square error (MSE) which is more interesting for practical purpose.**

Keywords—Localization, IR-UWB signaling, power delay profile, 2nd. order statistics, fingerprinting.

I. Introduction

The increasing popularity of wireless access infrastructure and mobile devices fulfils people's desire to access the multimedia services ubiquitously. Indoor positioning is one of the important techniques that help making context-aware services feasible [1]. In fact, many applications may benefit from relatively accurate indoor location information of mobile terminals to enhance existing services or provide new ones.

The inaccuracy of such localization techniques is mainly due to the propagation conditions imposed by the wireless channel: multipath and non line of sight (NLOS) conditions. In indoor environments, the NLOS propagation degrades severely the performance of conventional techniques (time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), signal strength (SS)...) and creates a need of development of more accurate mechanisms suited for these situations [2].

To alleviate this problem, location fingerprinting technique has been introduced to obtain optimal performance in multipath environment. The key idea is to store some signal information (fingerprint), from the whole area, in a database where the entries are the corresponding terminal locations. Location fingerprinting performs well for non-line-of-sight (NLOS) circumstances as it is able to exploit the channel diversity. Thus, it is suitable for indoor positioning, and LOS propagation is then no more required.

Generally, the deployment of fingerprinting based positioning systems can be divided into two phases: offline phase and on-line phase. During off-line stage, site survey is performed in the target environment to collect the fingerprints at some sampling locations. In the on-line stage, the positioning techniques process the received signal from mobile terminal and calculate the estimated location coordinates based on the knowledge built during the off-line stage.

To constitute a signature or a fingerprint, several types of information can be used such as the received signal strength, angular power profile (APP) and power delay profile (PDP) [3], [4]. Several types of pattern-matching algorithms may then be employed with the objective to give the position of the mobile station with the weakest location error (least square error, likelihood probability...).

Recently, UWB signaling has grown in popularity since the Federal Communications Commission (FCC) regulations in the United States have defined emission masks for UWB signals [5]. The FCC ruling allows for coexistence with traditional and protected radio services and enable the potential use of UWB transmission without allocated spectrum. This is achieved by constraining UWB transmission systems to operate at a very low spectral density, sensibly equal to the power spectral density of thermal noise at the receiver. Thus, interference from UWB transmitters to others UWB users as well as other wireless systems with overlapping spectrum bandwidth resembles thermal noise. As result, scarce spectrum transmitter may be used more efficiently. The widely used form of UWB signaling is based on impulse radio (IR) [6].

IR-based UWB (IR-UWB) technology employs pulses of very short durations ($\leq$ ns) with very low spectral densities. It is resistant to channel multipath and has very good time-domain resolution allowing for location and tracking applications, and is relatively low-complexity and low-cost. Due to its high temporal resolution and its low range, UWB signaling is by nature a good candidate to provide accurate position information in indoor environments. Several works have considered its ranging capabilities to design localizations algorithms, [7], [8] to cite few.

In this work, we analyze the performances of some location fingerprinting techniques when using UWB signaling. Many works in the literature have considered the performances limitations of some localizations techniques, most of them have considered the conventional or the direct ones (TOA, TDOA, AOA, SS...), and the performances limitations were mainly characterized in terms of lower bounds on location error. The positioning problem for cellular networks is addressed in [9], UWB localizations performances limits in [10], and cooperative wireless sensor networks positioning is

[1]The work reported herein was partially supported by the European projects E2R and SENDORA and National projects GRACE and IDROMEL.

investigated in [11]. For fingerprinting techniques, the performances characterization is usually achieved by mean of time-consuming computer's simulations or costly measurements.

In this paper, we give an analysis of the performances of two fingerprinting-based localization schemes using IR-UWB signaling. The first scheme uses channel's power delay profile as fingerprints and least square error as matching function. The second one use channel 2nd. order statistics as fingerprints and maximum likelihood estimation as matching function.

The analysis allows us to model some key parameters as the grid dimensions and the number of samples in building the database, which help in selecting optimal setup of the localization system offline. The performances limitations are given in term of upper bound on the mean square error (MSE) which is more interesting for practical purpose.

The paper is organized as follows, Section I introduces the system model, Section II the PDP fingerprinting performances analysis, Section III the 2nd. order statistics fingerprinting performances, numerical results are presented in Section IV, and concluding remarks in Section V.

II. System Model

We consider an indoor wireless local area network, with only one access point (AP) that is always visible throughout the area under consideration. A square grid of dimension (D, D) is defined over the two-dimensional floor, the grid spacing is given by Δ and results in M^2 squares, $M = D/\Delta$. Without loss of generality, we assume M integer. The locations' fingerprints are limited to the points on the center of each resulting square. The AP is assumed to be in the center of the grid with coordinates $(0, 0, Z)$, $Z > 0$, and each fingerprint's location k is assumed to have coordinates $(x_k, y_k, 0)$. We denote by $\mathcal{M}$ the set of all fingerprints' location.

Let $s(t) = \sqrt{\frac{E_p}{T_p}}p(t)$ be the transmitted IR-UWB single-pulse one-shot signal, with E_p been the pulse energy, $p(t)$ is the transmitted pulse of duration T_p with $\int_0^{T_p} p(t)^2 dt = 1$, and $W_b = 1/T_p$ the signal bandwidth. Propagation studies for IR-UWB signals have shown that they undergo dense multipath environment producing large number of resolvable paths [12]. A typical model for the impulse response of a multipath channel is given by:

$$h(t) = \sum_{i=1}^{L} h_i \delta_{t,\tau_i} \tag{1}$$

where τ_i is the $i-th$ path delay and h_i is random variable modeling signal attenuation at τ_i, $\sum_{i=1}^{L} E[|h_i|^2] = 1$.
The received signal can then be written as:

$$r(t) = s(t) * h(t) + n(t) = \sqrt{\frac{E_p}{T_p}} \sum_{i=1}^{L} h_i p(t - \tau_i) \tag{2}$$

where T_d is the channel delay spread and $n(t)$ is complex Gaussian noise process with zero mean and power spectral density N_0. Since each component of y is a combination of many significant random variables we model it as non-stationary circular complex Gaussian process The autocorrelation function of y is given as:

$$\mathcal{K}_r(t, u) = \frac{E_p}{T_p} \sum_{i=1}^{L} E[|h_i|^2] p(t - \tau_i) p(u - \tau_i) + N_0 \delta_{t,u} \tag{3}$$

For every location (x, y) in the network area, $x, y \in [-D/2,\ D/2]$, we take an equi-spaced taped-channel model of length L, and we assume a degenerate representation K_r of $\mathcal{K}$, of dimension (L, L), whose entries are given as follows:

$$K_r^{x,y}(m, n) = \frac{E_p}{T_p} \sum_{i=1}^{L} E[|h_i^{x,y}|^2] p(\tau_m - \tau_i) p(\tau_n - \tau_i) + N_0 \delta \tau_m, \tau_n \tag{4}$$

We further define the diagonal elements of $K_r^{x,y}$ by:

$$K_r^{x,y}(i, i) = \ _{x,y}\sigma_i^2\ , i = 1 \ldots L \tag{5}$$

III. Channel's Power Delay Profile as Fingerprints

For every fingerprint's location k in $\mathcal{M}$, we take as fingerprint the vector F_k which is the average over N independent realization of the received signal r_k's power delay profile. Thus, the elements of F_k are given as follows:

$$f_k(i) = \frac{1}{N} \sum_{j=1}^{N} |r_j^k(i)|^2 \quad , \ i = 0 \ldots L \tag{6}$$

Given an observation r of the received signal and a fingerprint F_k's PDP, we define the score matching function as the Euclidian distance between the observation and the fingerprint information:

$$S(r, f_k) = \sqrt{\sum_{i=1}^{L} [|r(i)|^2 - f_k(i)]^2} \tag{7}$$

The location estimate $\hat{k}$ is then defined as the argument in $\mathcal{M}$ that minimize the score matching function:

$$\hat{k} = arg_{k \in \mathcal{M}}\ min\ \ S(r, f_k) \tag{8}$$

In the following, we are interested to derive an upper-bound on the MSE of the estimation error.
Conditioned on (x, y) being the location of the source of the received signal $r_{x,y}$, we define $P_{k,l}^{x,y}$ as the pairwise error probability (PEP) of deciding that the mobile terminal position (x, y) is within the area of fingerprint l rather than the exact area of fingerprint k. This probability is expressed as follows

$$
\begin{aligned}
& P_{k,l}^{x,y}(err) = P(\hat{k} = l | k \text{ is the nearest fingerprint's location to } (x,y)) \\
= \quad & P(\hat{k} = l | x \in [x_k - \Delta/2, x_k + \Delta/2],\ y \in [y_k - \Delta/2, y_k + \Delta/2]) \\
= \quad & \prod_{j \in \mathcal{M}-\{l\}} P_k\left(S(r_{x,y}, f_l) < S(r_{x,y}, f_j)\right) \\
= \quad & \prod_{j \in \mathcal{M}-\{l\}} \left[1 - P_k\left(S(r_{x,y}, f_l) \geq S(r_{x,y}, f_j)\right)\right] \\
= \quad & \prod_{j \in \mathcal{M}-\{l\}} \left[1 - P_k\left(\sum_{i=1}^{L}\left[|r_{x,y}(i)|^2 - f_l(i)\right]^2 \right.\right. \\
& \left.\left. \geq \sum_{i=1}^{L}\left[|r_{x,y}(i)|^2 - f_j(i)\right]^2\right)\right] \\
\leq \quad & \prod_{l \in \mathcal{M}-\{l\}} \left[1 - \prod_{i=1}^{L} P_k\left(\left[|r_{x,y}(i)|^2 - f_l(i)\right]^2 \right.\right. \\
& \left.\left. \geq \left[|r_{x,y}(i)|^2 - f_j(i)\right]^2\right)\right]
\end{aligned} \tag{9}
$$

The $|r_{x,y}(i)|^2$ are Gamma distributed $\mathcal{G}(\alpha_i^{x,y}, \theta_i^{x,y})$ with shape parameter $\alpha_i^{x,y} = 1$ and scale parameter $\theta_i^{x,y} = {}_{x,y}\sigma_i^2$. Similarly, $f_j(i)$, $j \in \mathcal{K}$, $i = 1 \ldots L$, can be seen as Gamma-distributed $\mathcal{G}(\alpha_i^j, \theta_i^j)$ random variables (r.v.) with shape parameter $\alpha_i^j = N$ and scale parameter $\theta_i^j = \frac{{}_j\sigma_i^2}{N}$.
As the distribution of the sum of Gamma r.v. with different scale parameters is difficult to obtain, we can approximate it by another Gamma r.v. that has the same mean and variance. Thus $f_j(i) + f_k(i)$ could be seen as Gamma $\mathcal{G}(\alpha_i^{j+k}, \theta_i^{j+k})$ r.v with shape parameter $\alpha_i^{j+k} = \frac{N({}_j\sigma_i^2 + {}_k\sigma_i^2)^2}{{}_j\sigma_i^4 + {}_k\sigma_i^4}$ and scale parameter $\theta_i^{j+k} = \frac{{}_j\sigma_i^4 + {}_k\sigma_i^4}{N({}_j\sigma_i^2 + {}_k\sigma_i^2)}$.
The PEP can then be rewritten as

$$
\begin{aligned}
P_{k,l}^{x,y}(err) \quad \leq \quad & \prod_{l \in \mathcal{L}-\{l\}} \left[1 - \prod_{i=1}^{L} P_k\left(X_i^j - X_i^l \geq 0\right) P\left(R_i^{x,y} - X_i^{j+l} \geq 0\right)\right. \\
& \left. + P_k\left(X_i^j - X_i^l \leq 0\right) P\left(R_i^{x,y} - X_i^{j+l} \leq 0\right)\right]
\end{aligned} \tag{10}
$$

where $R_i^{x,y}$ are $\mathcal{G}(\alpha_i^{x,y}, 2\theta_i^{x,y})$, X_i^j are $\mathcal{G}(\alpha_i^j, \theta_i^j)$, and X_i^{j+k} are $\mathcal{G}(\alpha_i^{j+k}, \theta_i^{j+k})$. From [13], we have that for two Gamma r.v with parameters (α_1, θ_1) and (α_2, θ_2), the distribution of their difference is given by

$$
P(Z_1 - Z_2 \leq 0) \quad = \quad \frac{\theta_1^{\alpha_2}\theta_2^{\alpha_1}\ {}_2F_1\left(1, \alpha, \alpha_1 + 1, \frac{\theta_2}{\theta}\right)}{\alpha_1 B(\alpha_1, \alpha_2)(\theta)^{\alpha}} \tag{11}
$$

$$
\text{with} \qquad \alpha = \alpha_1 + \alpha_2\ , \quad \theta = \theta_1 + \theta_2 \tag{12}
$$

Where ${}_2F_1$ is the Gauss hypergeometric function.
The conditional probability of estimation error (on (x,y) in the area of k) is given by

$$
P_k^{x,y}(err) \quad \leq \quad \sum_{l \in \mathcal{M}-\{k\}} P_{k,l}^{x,y}(err) \tag{13}
$$

Assuming that the mobile terminal position is uniformly distributed inside each fingerprint's location area, the conditional probability of location estimation error is then given by

$$
P^k(err) = \frac{1}{\Delta^2}\int_{x_k - \frac{\Delta}{2}}^{x_k + \frac{\Delta}{2}} \int_{y_k - \frac{\Delta}{2}}^{y_k + \frac{\Delta}{2}} P_k^{x,y}(err)dxdy \tag{14}
$$

Assuming further that the mobile terminal position is uniformly distributed over the whole network area, the probability of location estimation error is then

$$
\begin{aligned}
P(err) \quad &= \quad \frac{1}{M^2\Delta^2}\sum_{k \in \mathcal{M}} P^k(err) \\
&= \quad \frac{1}{D^2}\int_{x_k - \frac{\Delta}{2}}^{x_k + \frac{\Delta}{2}} \int_{y_k - \frac{\Delta}{2}}^{y_k + \frac{\Delta}{2}} P_k^{x,y}(err)dxdy
\end{aligned} \tag{15}
$$

While the location estimation's MSE is

$$
\begin{aligned}
MSE_{err} \quad = \quad & \frac{1}{D^2}\sum_{k \in \mathcal{M}}\sum_{l \in \mathcal{M}} \int_{x_k - \frac{\Delta}{2}}^{x_k + \frac{\Delta}{2}} \int_{y_k - \frac{\Delta}{2}}^{y_k + \frac{\Delta}{2}} \\
& \left[(x - x_l)^2 + (y - y_l)^2\right] P_{k,l}^{x,y}(err)dxdy
\end{aligned} \tag{16}
$$

IV. CHANNEL'S 2ND. ORDER STATISTICS AS FINGERPRINTS

In order to base our decision on a maximum likelihood (ML) test, and assuming that the received signal at the AP is zero-mean complex Gaussian process, we use as fingerprint an estimate of the covariance matrix of the received signal aver N measurements or realizations of r. Thus, for each location $k \in \mathcal{M}$, the fingerprint is defined as the matrix F_k given by

$$
F_k = \frac{1}{N}\sum_{j=1}^{N} R_j R j^{\dagger} \tag{17}
$$

R denotes vector representation of r and $\dagger$ complex conjugate. Given an observation $R^{x,y}$ of the received signal and a fingerprint F_k, we define the score matching function as the log-likelihood that $R^{x,y}$ is distributed according to F_k

$$
S(r, f_k) \quad = \quad \log P(R_{x,y}|k) = -R_{x,y}^{\dagger}F_k^{-1}R_{x,y} - a - b_k \tag{18}
$$

$$
\text{Where} \qquad a = \frac{L}{2}\log(2\pi)\ ,\ b_k = \frac{1}{2}\log(\det(F_k))
$$

The location estimate $\hat{k}$ is then defined as the argument in $\mathcal{M}$ that maximize the matching score function

$$
\hat{k} = arg_{k \in \mathcal{M}}\ max;\ S(r, f_k) \tag{19}
$$

Conditioned on (x,y) being the location of the source of the received signal $R^{x,y}$, the PEP of deciding that the mobile terminal position (x,y) as in the area of fingerprint l rather than in the exact area of fingerprint k is given by

$$
\begin{aligned}
P_{l,j}^{x,y}(err) \quad &= \quad \prod_{l \in \mathcal{M}-\{l\}} P\left(S(r_{x,y}, f_l) > S(r_{x,y}, f_j)\right) \\
&= \quad \prod_{l \in \mathcal{M}-\{l\}} \left[1 - P\left(Z_{l,j}^{x,y} > b_l - b_j\right)\right],
\end{aligned} \tag{20}
$$

$$
where \qquad Z_{l,j}^{x,y} = R_{x,y}^{\dagger}Q_{l,j}R_{x,y} \tag{21}
$$

$$
Q_{l,j} = F_l^{-1} - F_j^{-1} \tag{22}
$$

$Z_{l,j}^{x,y}$ is a quadratic form on complex Gaussian random variables. We begin by making a Karhunen-Loeve decomposition of $R^{x,y}$ in the basis of its covariance matrix, $K_0 = U\Lambda U^{\dagger}$, where Λ is a diagonal matrix with eigenvalues of $K_R^{x,y}$ as diagonal elements, and U is a unitary matrix formed by the corresponding eigenvectors. $R^{x,y}$ can be written then as

$$R^{x,y} = U\Lambda^{\frac{1}{2}}\dot{R}^{x,y} \tag{23}$$

$$\text{where} \quad \dot{R}^{x,y} = \Lambda^{-\frac{1}{2}}U^{\dagger}R^{x,y} \quad , \quad K_{\dot{R}^{x,y}} = I \tag{24}$$

So we get

$$Z^{x,y}_{l,j} = \dot{R}^{x,y\dagger}\dot{Q}_{l,j}\dot{R}^{x,y} \tag{25}$$

$$\text{with} \quad \dot{Q}_{l,j} = \Lambda^{\frac{1}{2}}U^{\dagger}Q_{l,j}U\Lambda^{\frac{1}{2}} \tag{26}$$

As F_l and F_j are Hermitian, $\dot{Q}_{l,j}$ is also Hermitian and can be decomposed also as $VMV^{\dagger}$ where V is an orthonormal matrix of eigenvectors of $\dot{Q}_{l,j}$ and M is a diagonal matrix of corresponding eigenvalues μ^i. We can thus write

$$Z^{x,y}_{l,j} = (V^{\dagger}\dot{R}^{x,y})^{\dagger}M(V^{\dagger}\dot{R}^{x,y}) = \sum \mu^i|\ddot{R}^{x,y}_i|^2 \tag{27}$$

Where

$$\ddot{R}^{x,y} = V^{\dagger}\dot{R}^{x,y} = V^{\dagger}\Lambda^{-\frac{1}{2}}U^{\dagger}R^{x,y} \tag{28}$$

$$K_{\ddot{R}^{x,y}} = VK_{\dot{R}^{x,y}}V^{\dagger} = I \tag{29}$$

As $R^{x,y}_i$ are circular complex Gaussian random variables $CN(0,1)$, the random variables U_i defined as $U_i = 2|\ddot{R}_i^{x,y}|^2$ are independent chi-square random variables with two degrees of freedom $\chi(2)$. We have thus expressed $Z^{x,y}_{j,l}$ as weighted sum of N independent Chi-square random variables. We split the set of eigenvalues as $a^i = \{\mu^i \ , \ \mu^i \geq 0\}$ and $b^i = \{|\mu^i| \ , \ \mu^i < 0\}$. $Z^{x,y}_{j,l}$ can then be given as

$$Z^{x,y}_{j,l} = {}_1Z^{x,y}_{j,l} - {}_2Z^{x,y}_{j,l} \tag{30}$$

$$\text{Where} \quad {}_1Z^{x,y}_{j,l} = \sum \frac{a^i}{2}U_i \tag{31}$$

$${}_2Z^{x,y}_{j,l} = \sum \frac{b^i}{2}U_i \tag{32}$$

We can use again the Gamma approximation to express ${}_1Z^{x,y}_{j,l}$ and ${}_1Z^{x,y}_{j,l}$ as Gamma distributed variables $G_1(\alpha_1,\beta_1)$ and $G_2(\alpha_2,\beta_2)$, where

$$\alpha_1 = \frac{(\sum a^i_x)^2}{\sum (a^i_x)^2} \quad , \quad \beta_1 = \frac{\sum (a^i_x)^2}{\sum a^i_x} \tag{33}$$

$$\alpha_2 = \frac{(\sum b^i_x)^2}{\sum (b^i_x)^2} \quad , \quad \beta_2 = \frac{\sum (b^i_x)^2}{\sum b^i_x} \tag{34}$$

The conditional error probability error becomes

$$\begin{aligned} P^{x,y}_{j,l}(err) &= \prod_{l\in\mathcal{M}-\{l\}} \left[1 - P\left({}_1Z^{x,y}_{l,j} - {}_1Z^{x,y}_{l,j} > b_l - b_j\right)\right] \\ &\leq \prod_{l\in\mathcal{M}-\{l\}} \left[1 - P\left({}_1Z^{x,y}_{l,j} > b_l\right)P\left({}_1Z^{x,y}_{l,j} \leq b_j\right)\right] \end{aligned} \tag{35}$$

Following the same derivation as in the preceding section, we can express the estimation probability of error and the estimation MSE.

V. Numerical Results

We performed simulations for an UWB system with $N = 40$ subcarriers. Usually an UWB indoor propagation channel can be identified by different characteristics that are drown from a traveling signals. Such characteristics help to identify the impulse response of a given medium, and in our case some of those characteristics would be used as fingerprints for the localization system.

The sampling frequency, $F_s = 1$ GHz, is selected to be over twice the highest signal frequency. The dimensions of the room are designated as 6 m $\times$ 6 m to simulate a typical indoor office environment so that the results can be verified against earlier measurement-based statistical studies. The antennas are assumed to be omni-directional point sources, and their dispersive effects are neglected.

Fig. 1 and 2 depict the mean square error (MSE) performances of single-antenna multiband UWB system as functions of average SNR per bit in decibels (dB), for various separation distance ($\Delta = 50$ cm, $\Delta = 1$ m and $\Delta = 2$ m). The pulse is of duration $T_p = 1ns$ and the observation period is of length $T_f = 100ns$. The SNR is defined as SNR $= \frac{E_pT_p}{T_fN_0}$.

We observe that the performances of UWB system in PDP fingerprints and 2nd. order statistics fingerprints are almost the same, and they are close to the exact PEP calculation in 10 and 20, respectively. We can observe that the performance becomes better as the separation distance decreases. When $\Delta = 2$ m, the obtained MSE using power delay profile fingerprints can achieve 3 10^{-2} at SNR $= -2.5$ dB; while when the separation distance increases to 50 cm, the obtained MSE can achieve 3 10^{-2} even at SNR $= 2.5$ dB.

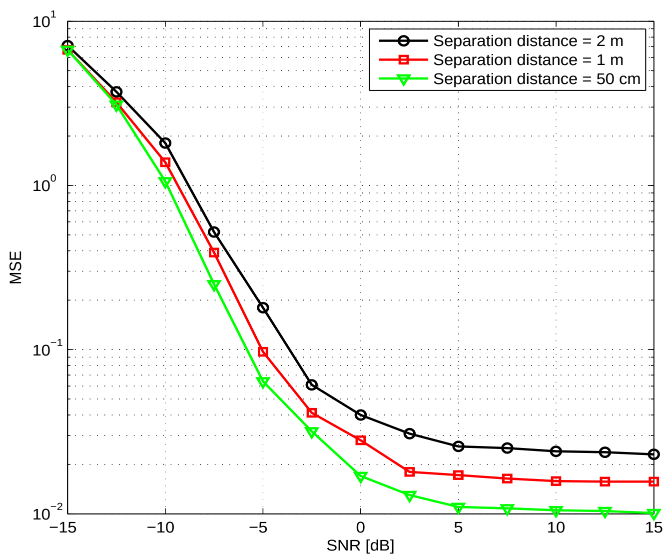

Fig. 1. MSE versus SNR using power delay profile fingerprints for various separation distance ($\Delta = 50$ cm, $\Delta = 1$ m and $\Delta = 2$ m)

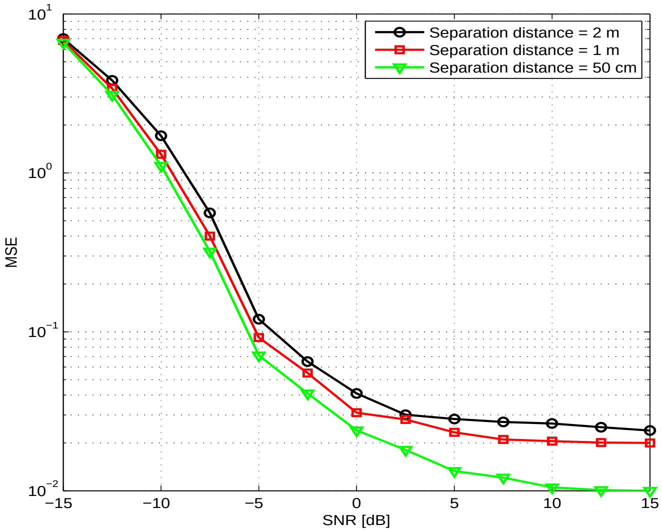

Fig. 2. MSE versus SNR using 2nd. order statistics fingerprints for various separation distance ($\Delta = 50$ cm, $\Delta = 1$ m and $\Delta = 2$ m)

VI. Conclusion

To conclude, we recapitulate by saying that this paper presented a localization system based on two fingerprinting techniques and using UWB. The first technique uses channel's power delay profile as fingerprints and least square error as matching function. The second one use channel 2nd. order statistics as fingerprints and maximum likelihood estimation as matching function. The obtained results showed high accuracy. The system performance seams to take advantage of the UWB propagation characteristics in the indoor channel. Nevertheless, and based on the current results, we expect a good performance of the higher complexity system.

References

[1] M. Triki, D. T. M. Slock, V. Rigal, P. Franois, "Mobile terminal positioning via power delay profile fingerprinting: reproducible validation simulations", In VTC Fall 2006, 64th IEEE Vehicular Technology Conference 2006, 2528 September 2006, Montral, Canada.

[2] M. Wax, and T. Kailath, "Decentralized Processing in Sensor Arrays", In IEEE trans. on Acoustics, Speech, and Signal Processing, Vol.33, Issue 5, pp. 1123-1129, Oct. 1985.

[3] S. Ahonen, and P. Eskelinen, "Mobile Terminal Location for UMTS", In IEEE Aerospace and Electronic Systems Magazine, Vol.18, Issue 2, pp. 23-27, Feb. 2003.

[4] S. Ahonen, and P. Eskelinen, "Performance Estimations of Mobile Terminal Location with Database Correlation in UMTS Networks", In Proc. of International Conf. on 3G Mobile Communication Technologies, pp. 25-27, June 2003.

[5] Federal Communications Commission, Cognitive Radio Technologies Proceeding (CRTP), http://www.fcc.gov/oet/cognitiveradio/.

[6] E. A. Homier and R. A. Scholtz, "Rapid acquisition of ultra-wideband signals in the dense multipath channel", IEEE Conference on UWB Systems and Technologies, pp. 245-250, May 2002.

[7] JY. Lee and R.A. Scholtz, "Ranging in a dense multipath environment using an UWB radio link", IEEE Trans. Select. Areas Commun., vol. 20, no. 9, pp. 16771683, December 2002.

[8] B. Denis, J. Keignart, and N. Daniele, "Impact of NLOS propagation upon ranging precision in UWB systems", In Proc. IEEE Conf. Ultra Wideband Systems and Technologies (UWBST03), pp. 379383, November 2003.

[9] F. Gustafsson and F. Gunnarsson, "Mobile positioning using wireless networks", IEEE Signal Processing Mag., vol. 22, no. 4, pp. 4153, July 2005.

[10] S. Gezici, Z. Tian, G.B. Giannakis, H. Kobayashi, A.F. Molish, H.V. Poor, and Z. Sahinglu, "Localization via ultra-wideband radios", IEEE Signal Processing Mag., vol. 22, no. 4, pp. 7084, July 2005.

[11] N. Patwari, A.O. Hero III, J. Ash, R.L. Moses, S. Kyperountas, and N.S. Correal, "Locating the nodes", IEEE Signal Processing Mag., vol. 22, no. 4, pp. 5469, July 2005.

[12] M. Z. Win and R. A. Scholtz, "On the energy capture of ultrawide bandwidth signals in sense multipath environments", IEEE Communications Letters, vol. 2, pp. 245247, 1998.

[13] M.K. Simon and M.-S. Alouini, "On the difference of two chi-square variates with application tooutage probability computation", IEEE Transactions on Communications, Vol. 49, PP. 1946-1954, 2001.