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INDOOR LOCATION BASED ON IEEE 802.11 ROUND-TRIP TIME MEASUREMENTS WITH TWO-STEP NLOS MITIGATION

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Abstract—This paper presents a comprehensive location scheme in a rich multipath environment. It is based on the estimation of the distance between two wireless nodes in line-of-sight (LOS) from the best statistical estimator of the round-trip time (RTT), assuming a linear regression as the model that best relates this statistical estimator to the actual distance. As LOS cannot be guaranteed in an indoor environment, the effect of non-line-of-sight (NLOS) is mitigated by a two-step correction scheme. At a first step, the severe NLOS error is corrected from distance estimates applying the prior NLOS

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measurement correction (PNMC) method. At a second step, a new multilateration technique is implemented together with received signal strength (RSS) information to minimize the difference between the estimated position and the actual one. The location scheme coupled with measurements in a real indoor environment demonstrates that it outperforms the conventional time-based indoor location schemes using neither a tracking technique nor a previous calibration stage of the environment and no need for time synchronization between wireless nodes.

1. INTRODUCTION

Indoor positioning is one of the challenging problems being faced today, which has numerous commercial and government applications [1]. For areas where there is a line-of-sight (LOS) to satellites, the GNSS (Global Navigation Satellite System) provides a good estimate (within a few meters) of a mobile user (MU) location. However, signals coming from satellites cannot be currently used in most indoor environments due to the fact that they are not strong enough to penetrate most materials [2]. Hence, alternative wireless infrastructures which offer strong signals should be used. Up to date, few wireless infrastructures which operate in indoor environments are as extensively deployed and used as IEEE 802.11, a reason that wireless technology is the best candidate for the development of indoor location schemes. Moreover, the addition of positioning capabilities to such widespread communications network could open up interesting markets. In this paper, a location scheme for indoor environments using the IEEE 802.11 wireless infrastructure is proposed.

Whichever indoor wireless technology is involved, location schemes can be broadly classified according to the signal information used. Hence, the latter can be the measured Time of Arrival (TOA) [3, 5], Time Difference of Arrival (TDOA) [6], Angle of Arrival (AOA) [7] or Received Signal Strength (RSS) [8] of the MU's signal at the reference devices or anchors. Moreover, hybrid location techniques as TDOA and AOA [9], TOA and RSS [10] or DOA and RSS [11] can be exploited to improve the accuracy. In this paper, the low-cost printed circuit board (PCB) that has been presented in [12] is used as a measuring system. Thus, the TOA information of the wireless signal is obtained to estimate the distance between two wireless nodes. Specifically, instead of TOA, round-trip time (RTT) is measured in order to avoid the need for time synchronization between wireless nodes, which would entail a major increase in the complexity of the location scheme development.

Then, as proposed in [12], assuming a simple linear regression as the model which best relates the statistical estimator of the RTT to the actual distance between two wireless nodes in LOS, the statistical estimator that best fits that model is found with the aim of improving the accuracy achieved in distance estimates with that PCB in a LOS environment.

Unfortunately, the assumption that a direct sight exists between two wireless nodes in an indoor environment is an oversimplification of reality, where the complicated indoor wireless environment imposes big challenges; for example, the transmitted signal could only reach the receiver through reflected, transmitted, diffracted, or scattered paths [13, 14]. Known as the non-line-of-sight (NLOS) problem, that impairment is the dominant factor that degrades the accuracy of mobile positioning. From the literature, several solutions have been proposed to mitigate the effect of NLOS problem but they have been mainly discussed within cellular networks [4, 15–18]. In this paper, the prior NLOS measurement correction (PNMC) method [15] is put into practice in an indoor environment to alleviate the effect of severe NLOS on distance estimates.

To culminate the location scheme, the MU position estimate is performed in a real rich multipath indoor environment. Where, if the distance estimates to anchors were perfect, then three anchors, placed at any location would be sufficient to unambiguously determine the MU position in two-dimensions, using a simple multilateration method. However, as distance estimates are not perfect, a new multilateration method together with RSS information is proposed to minimize the difference between the MU position estimate and its actual position.

The paper is organized as follows. Section 2 proposes the best statistical estimator of the RTT assuming a linear regression model to relate that estimator with actual distance in LOS. Section 3 describes the mitigation of the severe NLOS effect on those distance estimates using the PNMC method. Section 4 presents a new multilateration method that smooths even more the effect of NLOS directly on the MU position to better estimate the actual one. Section 5 evaluates the performance of the new location scheme in a rich multipath indoor environment, and Section 6 summarizes the main conclusions.

2. RELATION BETWEEN ROUND-TRIP TIME MEASUREMENTS AND DISTANCE IN LINE-OF-SIGHT

According to [19], the distance resolution of a location system is determined by the bandwidth of the transmitted signal, 6.8 m in the IEEE 802.11b standard. High-precision location would require large transmission bandwidths and thus the use of multiple frequency channels. Moreover, if a PCB governed by a frequency clock is used to measure the RTT between two wireless nodes, the distance resolution is also hampered by that frequency clock. Additionally, even in a LOS environment, RTT measurements have a random behavior due to the error introduced by the standard noise from electronics in the measurement (which is always present). Therefore, to overcome the limitations in distance resolution and the effect of electronic errors, several statistical estimators of the RTT are going to be analyzed.

The PCB presented in [12] is used as measuring system to perform RTT measurements between an anchor and an MU device (the MU carries the PCB) for several distances from 2 to 40 m in a LOS environment, where both wireless nodes are placed on a cardboard box 1 m high each to guarantee the First Fresnel zone clearance. Therefore, a statistical value from a group of RTT measurements taken between two wireless nodes at a given distance is selected based on the estimator used. The latter will be representative of that distance between both nodes.

If a simple linear regression model is assumed to relate the statistical estimator with the actual distance [12], the way in which several statistical estimators of the RTT can be compared is by using the correlation coefficient (r^2). The latter indicates the percentage variation in the statistical estimators explained by the simple linear model. Therefore, the easiest method for dealing with actual distance is simply to take the statistical estimator with the highest correlation coefficient. Thus, $r^2_{d,\hat{d}}$ is used to compare the different statistical estimators, where d is the actual distance while $\hat{d}$ is the estimated distance after having applied the linear regression model to the statistical estimator.

Thus, assuming LOS, the linear regression used is as follows,

$$\hat{d} = \beta_0 + \widehat{RTT}_{LOS}\beta_1 \tag{1}$$

$$\hat{d} = d + \epsilon_{LOS} \tag{2}$$

where $\widehat{RTT}_{LOS}$ is the statistical estimator of the RTT hampered by measuring errors; β_0 and β_1 are the intercept and slope of the linear regression model respectively; and ϵ_{LOS} is the error introduced by the used estimator. The term ϵ_{LOS} can be modeled as a Gaussian random variable with zero mean and standard deviation σ_{LOS} since the estimators are asymptotically Gaussian, so

$$\epsilon_{LOS} \rightsquigarrow N(0, \sigma_{LOS}) \tag{3}$$

where the value of σ_{LOS} depends on the statistical estimator used.

In [12], due to the flexibility of the Weibull distribution when it models the RTT measurements distribution, it has been shown that the scale parameter of Weibull distribution (scale-W) provides better fit to the actual distance than the sample mean. In this paper, a better statistical estimator of the RTT performed in LOS is found through an analysis of the expression of the maximum likelihood estimator (MLE) of the scale-W. Thus, assuming that the shape parameter of the Weibull distribution (shape-W) is known, the scale-W can be easily estimated by using the MLE method as follows:

If $f(x;k,\lambda)$ is the probability density function of a Weibull (two-parameter) random variable x, then

$$f(x;k,\lambda) = \frac{k}{\lambda^k}\cdot x^{k-1}\cdot e^{-\left(\frac{x}{\lambda}\right)^k} \qquad x \geq 0 \tag{4}$$

where $k > 0$ is the shape-W and $\lambda > 0$ is the scale-W. Let $X_1, X_2, \ldots, X_n$ be a random sample of random variables with two-parameter Weibull distribution, k and λ. The likelihood function is

$$L(x_1,\ldots,x_n;k,\lambda) = \prod_{i=1}^{n} f(x_i;k,\lambda) \tag{5}$$

Therefore,

$$\begin{aligned}
\ln L(x_1,\ldots,x_n;k,\lambda) &= \sum_{i=1}^{n}\ln f(x_1,\ldots x_n;k,\lambda)\\
&= \sum_{i=1}^{n}\left(\ln\left(\frac{k}{\lambda}\right)+(k-1)\cdot\ln\left(\frac{x_i}{\lambda}\right)-\left(\frac{x_i}{\lambda}\right)^k\right)\\
&= n\cdot\ln\left(\frac{k}{\lambda}\right)+(k-1)\cdot\sum_{i=1}^{n}\ln\left(\frac{x_i}{\lambda}\right)-\sum_{i=1}^{n}\left(\frac{x_i}{\lambda}\right)^k\\
&= n\cdot(\ln(k)-\ln(\lambda))+(k-1)\cdot\left[-n\cdot\ln(\lambda)+\sum_{i=1}^{n}\ln(x_i)\right]-\sum_{i=1}^{n}\left(\frac{x_i}{\lambda}\right)^k\\
&= n\cdot\ln(k)+(k-1)\cdot\sum_{i=1}^{n}\ln(x_i)-n\cdot k\cdot\ln(\lambda)-\lambda^{-k}\cdot\sum_{i=1}^{n}x_i^k
\end{aligned} \tag{6}$$

thus,

$$\frac{\partial \ln L}{\partial\lambda} = -n\cdot k\cdot\frac{1}{\lambda}+k\cdot\frac{1}{\lambda^{k+1}}\cdot\sum_{i=1}^{n}x_i^k \tag{7}$$

in order to find the maximum, $\frac{\partial \ln L}{\partial \lambda} = 0$ hence, the MLE of the scale-W is

$$\hat{\lambda} = \left[\frac{1}{n} \sum_{i=1}^{n} x_i^k \right]^{\frac{1}{k}} \tag{8}$$

This expression is known as the Hölder mean [20]. This mean is a generalized mean of the form,

$$M_p(x_1, x_2, \ldots, x_n) = \left[\frac{1}{n} \sum_{i=1}^{n} x_i^p \right]^{\frac{1}{p}} \tag{9}$$

where the parameter p is an affinely extended real number; n is the number of samples and x_i are the samples with $x_i \geq 0$. Therefore, the MLE of the scale-W ($\hat{\lambda}$) is the Hölder mean (M_k) with the shape-W as p parameter. Some common named means that are special cases of the Hölder mean are the minimum ($M_{-\infty}$), harmonic mean (M_{-1}), geometric mean (M_0), arithmetic mean (M_1), quadratic mean (M_2) or maximum (M_∞).

From RTT measurements performed in a LOS environment, any of the estimators of the form M_p with $p \in \{-\infty, -1, 0, 1, 2, \infty\}$ has a correlation coefficient higher than M_k, where k is the shape-W. But, if an analysis of the correlation coefficient is performed among statistical estimators of the form $M_{r \cdot k}$ and $M_{\frac{k}{r}}$ with $r \in \mathbb{Z}$ in $[1, 10]$, it is easy to see that the correlation coefficient reaches its maximum value with M_{3k} as statistical estimator, specifically for M_{3k}, $r^2_{d,\hat{d}} = 0.977$, which indicates that the linear regression model nearly fits that statistical estimator perfectly. Similarly, Fig. 1 shows how the cumulative probability of errors in terms of distance estimation reaches its minimum value at M_{3k}. Therefore, it can be concluded that M_{3k} is the statistical estimator which provides the best fit to actual distance if a simple linear regression model is used to relate the statistical estimator to the actual distance.

Once M_{3k} is found as the statistical estimator of the RTT that best fits actual distance, its performance is compared to other solutions cited for distance estimation to evaluate the goodness of the proposed one (Fig. 2). The same two wireless nodes have been used in the same LOS environment for all the solutions analyzed.

As it is well known, the distance between two wireless devices causes an attenuation in the RSS values. This attenuation is known as path loss, and it is modeled to be inversely proportional to the distance

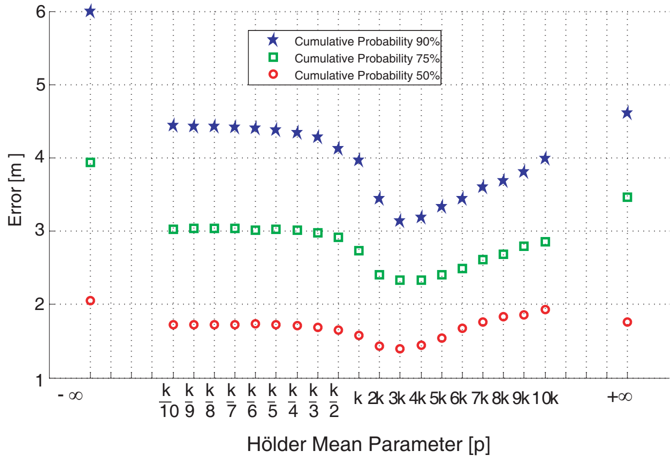


Figure 1. Three representative cumulative probabilities of errors in terms of distance estimation performed for different statistical estimators of the form $M_{r \cdot k}$ and $M_{\frac{k}{r}}$ with $r \in \mathbb{Z}$ in $[1, 10]$ and k the shape-W.

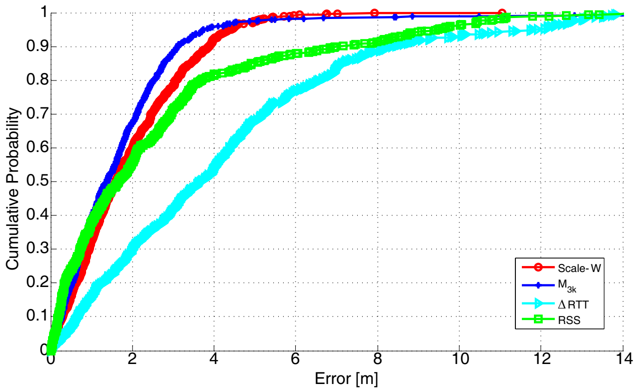


Figure 2. CDFs of errors in terms of distance estimation performed with three different statistical estimators cited (RSS, Scale-W linear regression and ΔRTT based) and the one proposed in this paper (M_{3k} linear regression based).

between both devices raised to a certain exponent [21]. Thus, according to [8] the distance between two wireless nodes can be estimated by

$$\hat{d} = 10^{\frac{P_{ref}-P}{10\alpha}} \tag{10}$$

where P_{ref} is the RSS measured in logarithmic units at 1 m; P is the RSS measured in logarithmic units at the actual distance and α is the path loss exponent. According to [22], for any distance under 20 m in LOS, α is recommended to be 2. Therefore, having taken this value for the path loss exponent and from the RSS value measured between both devices, the distance between the two wireless nodes can be estimated by (10). Fig. 2 shows the cumulative distribution function (CDF) of the error in distance estimated. As it could be expected, this is a good RSS-based distance estimation in LOS, where an error lower than 3 m for a cumulative probability of 75% is achieved for this particular LOS environment. But, as shown in Fig. 2, when it is compared to other distance estimation methods, propagation delays correlate more closely with distance than RSS-based.

Another solution cited to estimate distances is proposed in [23] where it uses a measuring system similar to the one proposed in this paper. The estimation of the distance is made by halving the ΔRTT, which corresponds to the pure propagation portion of the RTT. Specifically,

$$\Delta RTT = \left(\eta - \frac{\sigma}{3}\right) - \eta_0 \tag{11}$$

where η and σ are the sample mean and standard deviation of the RTT measurements respectively, and η_0 is the sample mean of RTT measurements at distance 0 m. This solution highly depends on the specific environment where the RTT measurements have been performed, which is the reason that its performance shown in Fig. 2 is not so good as the one presented in [23].

Finally, the CDF of errors in terms of distance estimation for the scale-W estimator (M_k) that was considered in [12] as better statistical estimator than the sample mean is also plotted in Fig. 2. As it can be seen, for a cumulative probability lower than 98%, the M_{3k} achieves a better accuracy than the Scale-W. But, for higher cumulative probabilities, due to a few outliers, the accuracy achieved by the M_{3k} is worse than the Scale-W.

3. MITIGATION OF THE NON-LINE-OF-SIGHT EFFECT FROM DISTANCE ESTIMATES

The assumption that LOS propagation conditions are present in an indoor environment is an oversimplification of reality. In such environments the transmitted signal could only reach the receiver through reflected, transmitted, diffracted, or scattered paths. Hence, these paths could positively bias the actual distance caused mainly by the blocking of the direct path or due to experiencing a lower propagation speed through obstacles [24]. Known as the NLOS problem, this positive bias has been deeply considered through the literature with the aim of mitigating its effect on distance estimates [15, 17, 18], but, in all of them the NLOS is mainly discussed within the cellular networks. Note that such techniques usually assume that the bias for the NLOS range measurements changes over time and has larger variances than LOS range measurements [25], assumptions that could not be assured in an indoor environment [26]. In this paper, the feasibility of the PNMC method presented in [15] is analyzed in an indoor environment, taking the PCB proposed in [12] as measuring system, M_{3k} as statistical estimator of the RTT and the simple linear regression as the model to relate M_{3k} to the actual distance.

The PNMC method relies on the statistical distribution of NLOS errors and on the major variance that NLOS errors present with respect to LOS. The distribution type of NLOS errors depends on the particular environment. Hence, it can follow different statistical distributions such as Gaussian, Exponential, Gamma, etc. [15]. Regarding the distribution, its parameters can be assumed to be constant in that particular environment. Moreover, those parameters can be obtained before the process of getting distance estimates [27] or directly from the estimated delay spread at that moment [28]. In this paper, those parameters have been obtained beforehand by a campaign of RTT measurements in NLOS.

Thus, assuming NLOS, let $\hat{d}$ be the estimated distance between two wireless nodes

$$\hat{d} = d + \epsilon_{LOS} + \epsilon_{NLOS} \tag{12}$$

where d is the actual distance; ϵ_{LOS} describes the measuring error and the term ϵ_{NLOS} is the error due to the lack of direct sight between both nodes. Once M_{3k} has been chosen as the best statistical estimator of the RTT when both nodes are in LOS, the terms which define the linear model, β_0 and β_1, are fixed, and the term ϵ_{LOS} is observed to be Gaussian distributed with zero mean and a standard deviation $\sigma_{LOS} = 1.5\,\text{m}$. As said before, the random variable ϵ_{NLOS} depends on the particular environment where the MU is going to be located. In this paper, that environment is the second floor of the Higher Technical School of Telecommunications Engineering, University of Valladolid (Spain), a real rich multipath indoor environment with several offices, laboratories and people walking around (see Fig. 3). From an exhaustive campaign of RTT measurements in NLOS, the term ϵ_{NLOS} is considered to be exponentially distributed, thus

$$\epsilon_{NLOS} \rightsquigarrow Exponential(\beta) \tag{13}$$

where $\beta = 0.3\,\mathrm{m}^{-1}$ is the value that, in general, best fits the distribution with ϵ_{NLOS}, which means that the standard deviation of ϵ_{NLOS} is $\sigma_{NLOS} = 3.3\,\mathrm{m}$, and it is equal to the mean ($\mu_{NLOS} = 3.3\,\mathrm{m}$). Once the distribution of ϵ_{NLOS}, σ_{NLOS} and σ_{LOS} have been characterized, the feasibility of the PNMC method can be analyzed. Note that the variance of ϵ_{NLOS} does not show as much deviation from variance of ϵ_{LOS} as it could be expected in an indoor environment [26], which is a reason that the feasibility of the PNMC method could be questionable in an indoor environment. But, as it will be proved, the PNMC method can improve the distance estimate by mitigating the effect of severe NLOS even in an indoor environment.

RTT measurements shown in Fig. 3 have been performed between an anchor fixed in a laboratory and an MU which was moving on the route shown. Any of the positions on the route has a direct sight to the anchor, situation that could possibly happen in any indoor environment with high probability. Therefore, the route followed shows different degrees of NLOS and no LOS combined with NLOS situations.

The PNMC method is applied to a record of distance estimates corresponding to a window size of 15 positions, sliding 5 positions each time, where each estimated distance works out after applying the linear regression model on the statistical estimators of the RTT, M_{3k}. The PNMC processing relies on the deviation, S, of distance estimates within the record. As it is shown in [15] S depends on the NLOS ratio, r, present in that record. That dependence can be approximated by

$$r \approx \frac{2S\sqrt{\sigma^2_{LOS} + 0.5\sigma^2_{\mathrm{NLOS}} + \sqrt{\mu_{\mathrm{NLOS}}}} - 2\sigma^2_{\mathrm{LOS}} - 0.5\sigma^2_{\mathrm{NLOS}} - 2\sqrt{\mu_{\mathrm{NLOS}}}}{\sigma^2_{\mathrm{NLOS}}} \tag{14}$$

whereas ϵ_{NLOS} is considered to be exponentially distributed, $\mu_{NLOS} = \sigma_{NLOS}$.

Thanks to the knowledge of the severe NLOS ratio that is present in the record, it is known that $r \cdot 100\%$ of distance estimates come from severe NLOS propagation. Such distance estimates will be corrected based on the way in which ϵ_{NLOS} is distributed. Thus, the $r \cdot 100\%$

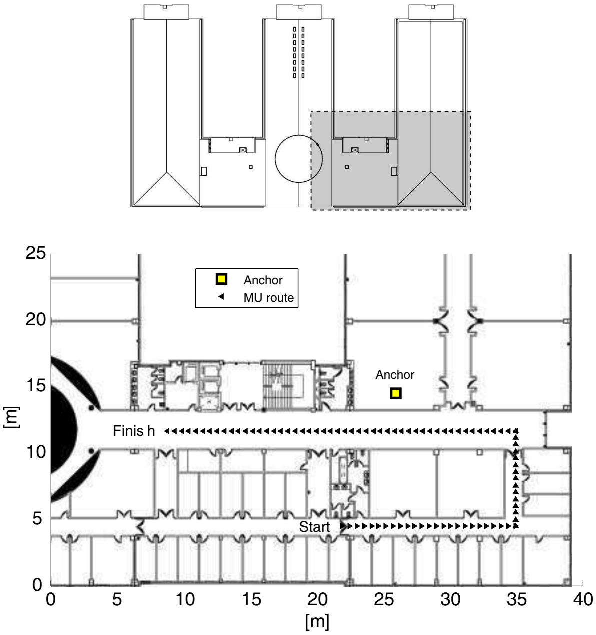
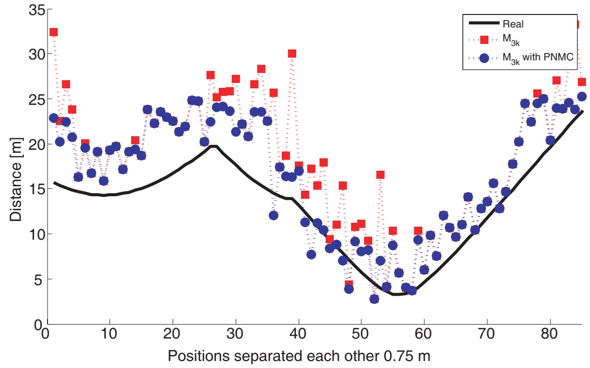


Figure 3. Second floor of the Higher Technical School of Telecommunications Engineering, University of Valladolid (Spain). Indoor environment where RTT measurements have been carried out.

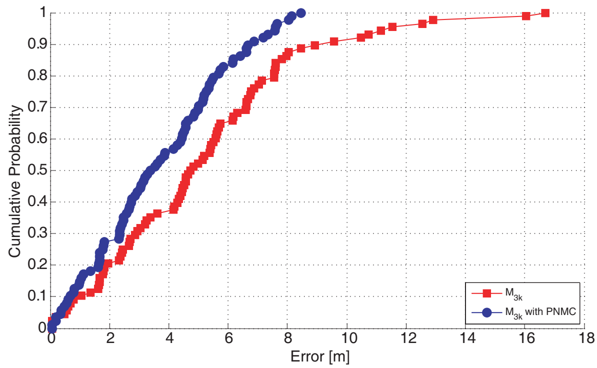
distance estimates are classified in segments, according to their values, and each one of them is corrected by subtracting the expected error in that segment [15].

Figure 4(a) shows the actual distance from the MU to the anchor at each position through the route shown in Fig. 3. The distance estimate, in red, at each position is shown by using M_{3k} as statistical estimator of the RTT, having applied the linear regression model. As it is observed in Fig. 4(a), due to the fact that the positions where the MU is going to be located do not have a direct sight to the anchor, distance estimates are almost always higher than the actual one. Therefore, PNMC method is going to correct distance estimates with severe NLOS. In blue, the distance estimates having applied the PNMC method on the computed distance estimates are shown. They are more similar to those that would be obtained in the absence of severe NLOS propagation.

It can be concluded that although the difference between σ_{LOS} and σ_{NLOS} is not so great, the presence of severe NLOS in the record is detected and corrected. As it is shown in Fig. 4(b) the improvement



(a) Correction of severe NLOS measurements with PNMC



(b) CDF

Figure 4. NLOS error mitigation from a record of distance estimates using a window size of 15 positions sliding 5 positions. (a) M_{3k} distance estimates before and after applying PNMC method. (b) Comparison of CDFs errors in distance estimate before and after applying PNMC method.

of applying the PNMC method can be observed through the CDF of errors in distance estimates. Generally speaking, the distance estimate can be improved on approximately 2 m for cumulative probabilities higher than 30% when applying the PNMC method.

4. FINDING THE BEST MOBILE USER LOCATION ESTIMATION UNDER NON-LINE-OF-SIGHT CONDITIONS

After having mitigated the effect of severe NLOS in distance estimates, those could be taken as inputs to find the MU location by multilateration. Multilateration is a common operation to find the MU location using its distance estimates to three or more known anchors. And as it is well known, additional capabilities can be included in multilateration methods to mitigate the effect of NLOS. Therefore, in this section a new multilateration technique based on the least-squared method to mitigate the NLOS effect on the MU position based on RSS information is proposed.

4.1. Least-squared Multilateration

In two-dimensions, multilateration is defined as the method to determine the intersections of M circles ($M \geq 3$) with centers the anchors position (O_{x_i}, O_{y_i}), and radius the distance estimate from the MU to each anchor in range $(\hat{d}_i)$, where both $i = 1, 2, \ldots, M$. Assuming that the number of distance estimates is greater than the minimum required ($M > 3$), an over-determined system of quadratic equations has to be solved to find the MU position. But in the common case, as $\hat{d}_i$ is impacted by noise, bias, and measurement error, it does not usually match the actual distance. Thus, the circles will not cut each other in a single point, which is a reason that the solution of that over-determined system can be found in the least-squared sense. Hence, the MU position $\mathbf{x} = [x, y]^T$ can be estimated by finding $\hat{\mathbf{x}}$ satisfying:

$$\hat{\mathbf{x}} = \arg\min_{x,y} \sum_{i=1}^{M} \left[\sqrt{(O_{x_i} - x)^2 + (O_{y_i} - y)^2} - \hat{d}_i \right]^2 \tag{15}$$

Solving (15) problem requires significant complexity, and it is difficult to analyze. Therefore, instead of using the circles as the equations to determine the MU location, the radical axes of all pairs of circles can be used. The radical axis of two circles is the locus of points at which tangents drawn to both circles have the same length. It can be easily obtained by subtracting the two involved circles' equations. In this way, the complex problem of solving an over-determined system of M quadratic equations is reduced to solve an over-determined system of $\frac{M(M-1)}{2}$ linear equations.

Let

$$\mathbf{Ax{=}b} \tag{16}$$

be the linear equation system with

$$\mathbf{A} = \begin{pmatrix} 2(O_{x_1} - O_{x_2}) & 2(O_{y_1} - O_{y_2}) \\ \vdots & \vdots \\ 2(O_{x_{M-1}} - O_{x_M}) & 2(O_{y_{M-1}} - O_{y_M}) \end{pmatrix} \tag{17}$$

and

$$\mathbf{b} = \begin{pmatrix} \hat{d}_2^2 - \hat{d}_1^2 - (O_{x_2}^2 - O_{x_1}^2) - (O_{y_2}^2 - O_{y_1}^2) \\ \vdots \\ \hat{d}_M^2 - \hat{d}_{M-1}^2 - (O_{x_M}^2 - O_{x_{M-1}}^2) - (O_{y_M}^2 - O_{y_{M-1}}^2) \end{pmatrix} \tag{18}$$

where $\mathbf{A}$ is a matrix of $\frac{M(M-1)}{2}$ rows and 2 columns described only by the anchors coordinates, while $\mathbf{b}$ is a vector of $\frac{M(M-1)}{2}$ rows represented by the distance estimates together with the anchor coordinates. In the least-squared sense the solution for (16) is done via

$$\hat{\mathbf{x}} = (\mathbf{A}^{\mathbf{T}}\mathbf{A})^{-1}\mathbf{A}^{\mathbf{T}}\mathbf{b} \tag{19}$$

where $\hat{\mathbf{x}}$ is an estimate of the actual MU position, assuming known anchors positions and having estimated the distance from the MU to each anchor in range. Note that as $\mathbf{b}$ depends on $\hat{d}_i$ and, in general, $\hat{d}_i$ does not match the actual distance; the solution of (19) has to be found in the least-squared sense. In this paper, Equation (19) is denoted as the least-squared multilateration method (LSM).

4.2. Weighting Least-squared Multilateration Based on Received Signal Strength

As in the previous subsection, it is assumed that the number of distance estimates is greater than the minimum required to determine a two-dimensional MU location ($M > 3$). Therefore, it is possible to perform C groups of those distance estimates in various ways subject to the constraint that the number of distance estimates involved in each group is no less than 3. Mathematically,

$$C = \sum_{i=3}^{M} \begin{pmatrix} M \\ i \end{pmatrix} \tag{20}$$

Applying the LSM method proposed in the previous subsection (19) for each of these combinations, C MU position estimates could be obtained, which are denoted as intermediate position estimates $\hat{\mathbf{x}}_{\mathbf{j}}$, $j = 1, 2, \ldots, C$. Thus, the final MU position estimate could be obtained by a linear combination of weighted intermediate position estimates.

The quality of the final MU position estimate ($\hat{\mathbf{x}}$) depends on the quality of the intermediate position estimates ($\hat{\mathbf{x}}_{\mathbf{j}}$, $j = 1, 2, \ldots, C$) and these depend on the quality of the distance estimates performed to each anchor in range ($\hat{d}_i$, $i = 1, 2, \ldots, M$). The bias error caused by severe NLOS in distance estimates is mitigated by applying the PNMC method. Thus, the final MU position estimate could be improved even more if it is performed by taking the best linear combination of weighted intermediate position estimates based on a certain criterion. This second step that mitigates the NLOS effect and finds the best MU location estimation is denoted as the weighted least-squared multilateration method (WLSM).

In [29], the criterion used to assign weights to intermediate position estimates is based on the sum of the residual squares, referred to as residual weighting algorithm (RWGH). Taking the residual as the difference between the distance estimation and the range between the intermediate position estimate and the anchor position. In this paper, the criterion chosen is based on giving more relevance to the distance estimations from anchors which are closer to the MU position. Generally speaking, the closer the anchor is, the lower the path length the signal has to travel, and thus, the lower the bias error in distance estimation is. Although the correlation between RSS and distance is difficult to predict in an indoor environment due to the unwieldy and dynamic nature of RSS, RSS information can give an idea about how close the anchor is. The fact that the criterion is based on using RSS information has the main advantage that no statistical models on NLOS channel conditions are needed, and it can be easily measured at the same time as the RTT measurements are being performed.

Let

$$W_{ght}(\hat{\mathbf{x}}_{\mathbf{j}}, S_j) = \left(\sum_{i \in S} [P_{ref} - P_i]^2\right)^{-1} \tag{21}$$

be the weight of the intermediate position estimate $\hat{\mathbf{x}}_{\mathbf{j}}$ performed over the anchors set S_j with $j = 1, 2, \ldots, C$. Where P_{ref} is the RSS measured in logarithmic units at 1 m, and P_i is the RSS measured in logarithmic units to the anchor i with $i \in S_j$, the higher W_{ght}, the closer the anchor and thus, the better the intermediate position estimate. However, the number of distance estimates in the C groups is different. Therefore, the normalized weight is defined to remove the dependence on the size of the group as:

$$\widetilde{W_{ght}}(\hat{\mathbf{x}}_{\mathbf{j}}, S_j) = \left(\frac{\sum\limits_{j=1}^{C} [P_{ref} - P_i]^2}{\text{Size of } S_j}\right)^{-1} \tag{22}$$

In consequence, the final MU position estimation is the linear combination of the intermediate position estimations weighted to their

$\widetilde{W_{ght}}$ as follows:

$$\hat{\mathbf{x}} = \frac{\sum_{j=1}^{C} \hat{\mathbf{x}}_{\mathbf{j}} \cdot \widetilde{W_{ght}}(\hat{\mathbf{x}}_{\mathbf{j}}, S_j)}{\sum_{j=1}^{C} \widetilde{W_{ght}}(\hat{\mathbf{x}}_{\mathbf{j}}, S_j)} \tag{23}$$

5. PERFORMANCE EVALUATION

The location scheme is evaluated through the RTT measurements performed into the second floor of the Higher Technical School of Telecommunications, having taken the PCB proposed in [12] as measuring system. In that rich multipath environment the proposed WLSM method is compared to other two multilateration methods cited, LSM and RWGH, with the purpose to illustrate the accuracy improvement of the one proposed.

As shown in Fig. 5, the campaign of measurements has been carried out following a route among offices, laboratories and few people walking around. As anchors, 8 identical wireless access points have been used with two omnidirectional rubber duck antennas vertically polarized to each other in diversity mode. Anchors were configured to send a beacon frame 100 ms each at constant power on frequency channel 1 (2.412 GHz). As MU, an IEEE 802.11b WLAN cardbus adapter has been used with two on-board patch antennas in diversity mode. Diversity circuitry determines which antenna has better reception and switches it on in a fraction of a second while it turns off the other antenna. Therefore, both antennas are never on at the same time. The PCB was connected to the WLAN cardbus. Both, anchors and cardbus adapter, can be found on most IEEE 802.11 WLANs.

At a first approach, LSM method is applied at each actual position to estimate the MU position. The distance after having applied the linear model to the M_{3k} estimator (1) is taken as the estimation of the distance to each anchor in range. Thus, the estimation of the MU position is the one that minimizes (in least-squared sense (19)) the distance to each one of the radical axis performed among all pairs of circles, which center the anchors position and radius of the estimated distance. As a direct sight between the MU and anchors cannot be assured in an indoor environment, the effect of NLOS positively biases the distance estimates. Hence, PNMC method is applied to correct the effect of the severe NLOS on distance estimates. Thus, implementing LSM method together with PNMC method the accuracy on finding the MU position is improved. Finally, assuming the number of distance estimates is greater than the minimum required, a second step to mitigate the effect of NLOS can be implemented by applying the WLSM method. That method relies on assigning weights to intermediate position estimates based on RSS information (23). The effect of applying two-step NLOS mitigation works out in an accuracy improvement of the MU position estimate. The WLSM method is compared to the LSM and RWGH methods cited through the CDF of errors in terms of the estimation of the MU position in order to illustrate the performance improvement of the one proposed.

Figure 5 shows the MU position estimates having used the LSM, PNMC & LSM, PNMC & RWGH and PNMC & WLSM methods. The actual positions of the MU correspond to the black dots. Those positions describe a route along the corridors where the distance between each pair of continuous ones is approximately 0.75 m. The multilateration positions obtained by using the LSM and PNMC & LSM methods are shown in cyan and red, respectively, PNMC & RWGH multilateration positions in blue, while the PNMC & WLSM method positions have been shown in green. Whichever the multilateration method is used, all of the MU position estimates are close enough to the actual ones. Therefore, any of the multilateration methods together with the PNMC method could be

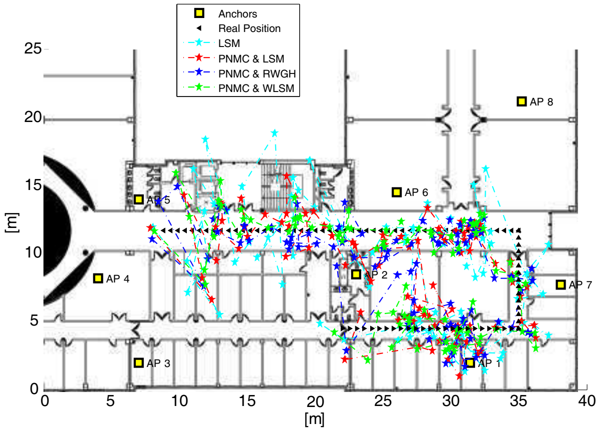


Figure 5. Multilateration obtained in the second floor of the Higher Technical School of Telecommunications Engineering, University of Valladolid (Spain). Black dots represent actual positions, cyan ones are LSM positions without PNMC, red, blue and green ones are LSM, RWGH and WLSM positions respectively after having applied PNMC method on distance estimates.

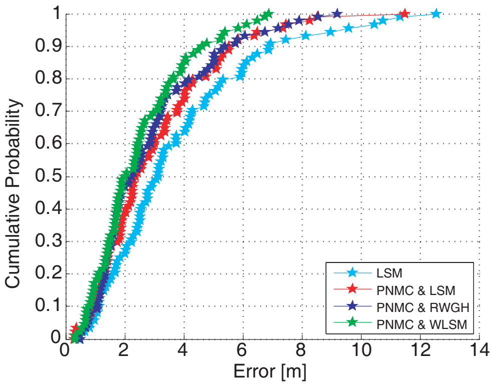


Figure 6. CDFs of errors in terms of MU position estimation performed with two different multilateration methods cited (LSM and RWGH) and the one proposed in this paper (WLSM). LSM method is proved taking as distance estimates those after having and not having applied the PNMC method. The other ones have been proved with the PNMC method.

used as an accurate indoor location scheme taking into account that neither a previous calibration stage nor any radio-map information about the environment has been used.

Figure 6 shows the CDF of errors in terms of the difference between the actual MU positions and the estimated ones to compare the accuracy achieved with the different solutions. As it could be expected, the LSM method presents the worst behavior due to that the NLOS effect is not mitigated from distance estimates. LSM method together with PNMC method improves the CDF because the severe NLOS effect is corrected from distance estimates. Finally, although RWGH and WLSM methods are based on different criteria, any of them with the PNMC method presents a slight improvement as compared to LSM together with PNMC, because both methods implement a second step to mitigate the NLOS effect. From results shown in Fig. 6, it can be concluded that the WLSM method, which uses the criterion based on RSS information, obtains better results than RWGH method, which uses the criterion based on residuals. Therefore, as it is shown in Fig. 6, the best choice would be the WLSM method together with the PNMC method which reaches an error lower than 4 m for a cumulative probability of 85%.

6. CONCLUSION

In this paper, a complete location scheme based on RTT measurements is proposed, analyzed and put into practice in a rich multipath indoor environment. The PCB proposed in [12] has been taken as RTT measuring system, and an IEEE 802.11 wireless infrastructure, already deployed, has been used as indoor wireless technology.

At a first step, distance estimation between two wireless nodes in LOS has been analyzed. Thus, assuming a simple linear regression as the model which relates the statistical estimator to actual distance, the M_{3k} has been found as the best statistical estimator of the RTT. M_{3k} is characterized by a correlation coefficient of 0.977, thus, it can be concluded that M_{3k} nearly fits the actual distance perfectly. At a second step, distance estimation between two wireless nodes has been analyzed in the NLOS indoor environment. Hence, the PNMC method has been applied to correct the effect of severe NLOS. An improvement of about 2 m for cumulative probabilities higher than 30% has been achieved after applying the PNMC method. At a final step, the MU position has been estimated using a new multilateration method, WLSM, which implements an NLOS mitigation technique based on RSS information.

The performance of that indoor location scheme has been evaluated in a real rich multipath indoor environment. The error achieved in the estimation of the MU position has been lower than 2 m for a cumulative probability of 50%. Note that the feasibility of using the location scheme has been proposed without any tracking technique or a previous calibration stage about the environment which could improve the positioning accuracy. For the WLSM method, the only premise it has been assumed is that the number of distance estimates is greater than the minimum required.

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REFERENCES

1. Pahlavan, K., X. Li, and J.-P. Mäkelä, "Indoor geolocation science and technology," *IEEE Communication Magazine*, Vol. 40, 112–118, 2002.

2. Lachapelle, G., "GNSS indoor location technologies," *Journal of Global Positioning Systems*, Vol. 3, No. 1–2, 2–11, 2004.
3. Golden, S. A. and S. S. Bateman, "Sensor measurements for Wi-Fi location with emphasis on time-of-arrival ranging," *IEEE Trans. on Mobile Computing*, Vol. 6, No. 10, 1185–1198, Oct. 2007.
4. Mak, L. C. and T. Furukawa, "A Time-of-arrival-based positioning technique with Non-line-of-sight mitigation using low-frequency sound," *Journal of Electromagnetic Waves and Applications*, Vol. 22, No. 5, 507–526, 2008.
5. Liew, S. C., K. G. Tan, and C. P. Tan, "Non-Taylor series based positioning method for hybrid GPS/Cellphone system," *Journal of Electromagnetic Waves and Applications*, Vol. 20, No. 6, 717–729, 2006.
6. Liew, S. C., K. G. Tan, and T. S. Lim, "Investigation of direct A-GPS positioning for hybrid E-OTD/GNSS," *Journal of Electromagnetic Waves and Applications*, Vol. 20, No. 1, 79–87, 2006.
7. Soliman, M. S., T. Morimoto, and Z. I. Kawasaki, "Three-dimensional localization system for impulsive noise sources using ultra-wideband digital interferometer technique," *Journal of Electromagnetic Waves and Applications*, Vol. 20, No. 4, 515–530, 2006.
8. Mazuelas, S., F. A. Lago, D. González, A. Bahillo, J. Blas, P. Fernández, R. M. Lorenzo, and E. J. Abril, "Dynamic estimation of optimum path loss model in a RSS positioning system," *Proceedings of Position, Location and Navigation Symposium*, 679–684, Monterrey, California, USA, Mar. 2008.
9. Wang, X., P. R. P. Hoole, and E. Gunawan, "An electromagnetic-time delay method for determining the positions and velocities of mobile stations in a GSM network," *Progress In Electromagnetics Research*, PIER 23, 165–186, 1999.
10. Hatami, A. and K. Pahlavan, "Hybrid TOA-RSS based localization using neural networks," *Proceedings of IEEE Global Telecommunications Conference*, Nov. 2006.
11. Tayebi, A., J. Gomez, F. S. De, Adana, and O. Gutierrez, "The application of ray-tracing to mobile localization using the direction of arrival and received signal strength in multipath indoor environments," *Progress In Electromagnetics Research*, PIER 91, 1–15, 2009.
12. Bahillo, A., J. Prieto, S. Mazuelas, R. M. Lorenzo, J. Blas, and P. Fernández, "IEEE 802.11 distance estimation based on RTS/CTS two-frame exchange mechanism," *Proceedings of Trans.*

on Vehicular Technology Conference, Barcelona, Spain, Apr. 2009.

13. Jiang, L. and S. Y. Tan, "A simple analytical path loss model for urban cellular communication systems," *Journal of Electromagnetic Waves and Applications*, Vol. 18, No. 8, 1017–1032, 2004.
14. Blas Prieto, J., P. Fernández Reguero, R. M. Lorenzo Toledo, E. J. Abril, S. Mazuelas Franco, A. Bahillo Martinez, and D. Bullid, "A model for transition between outdoor and indoor propagation," *Progress In Electromagnetics Research*, PIER 85, 147–167, 2008.
15. Mazuelas, S., F. A. Lago, J. Blas, A. Bahillo, P. Fernández, R. M. Lorenzo, and E. J. Abril, "Prior NLOS measurement correction positioning cellular wireless networks," *IEEE Trans. on Vehicular Technology*, Vol. 58, 2585–2591, Jun. 2009.
16. Seow, C. K. and S. Y. Tan, "Localization of omni-directional mobile device in multipath environments," *Progress In Electromagnetics Research*, PIER 85, 323–348, 2008.
17. Tang, H., Y. Park, and T. Qui, "NLOS mitigation for TOA location based on a modified deterministic model," *Research Letters in Signal Processing*, Vol. 8, No. 1, 1–4, Apr. 2008.
18. Wylie, M. P. and J. Holtzman, "The non-line of sight problem in mobile location estimation," *Proceedings of the 5th IEEE International Conference on Universal Personal Communications*, Vol. 2, 827–831, Cambridge, Mass, USA, Oct. 1996.
19. Chen, V. C. and H. Ling, *Time-frequency Transforms for Radar Imaging and Signal Analysis*, Artech House, Norwood, MA, USA 2002.
20. Bullen, P. S., *Handbook of Means and Their Inequalities*, Kluwer Academic Publishers, Dordrecht/Boston/London, 2003.
21. Pahlavan, K. and A. H. Levesque, *Wireless Information Networks*, John Wiley & Sons, Inc., New York, 1995.
22. *IEEE Standard for Information Technology — Telecommunications and Information Exchange Between Systems — Local and Metropolitan Area Networks — Specific Requirements — Part 11: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications: Amendment 8: Medium Access Control (MAC) Quality of Service (QoS) Enhancements*, IEEE Amendment to IEEE Std 802.11, 1999 Edition (Reaff 2003) IEEE Std 802.11e-2005, Nov. 2005.
23. Ciurana, M., F. B.-Arroyo, and F. Izquierdo, "A ranging system with IEEE 802.11 data frames," *Proceedings of IEEE Radio*

Wireless Symposium Conference, 133–136, Jan. 2007.

24. Allen, B., M. Dohler, E. Okon, W. Malik, A. Brown, and D. Edwards, Eds., *Ultra Wideband Antennas and Propagation for Communications, Radar, and Imaging*, John Wiley & Sons, West Sussex, UK, 2007.
25. Güvenç I., C.-C. Chong, F. Watanabe, and H. Inamura, "NLOS identification and weighted least-squares localization for UWB systems using multipath channel statistics," *EURASIP Journal on Advances in Signal Processing*, Vol. 2008, DOI: 10.1155/2008/271984, 2008.
26. Yarkoni, N. and N. Blaunstein, "Prediction of propagation characteristics in indoor radio communication environment," *Progress In Electromagnetics Research*, PIER 59, 151–174, 2006.
27. Li, C. and W. Zhuang, "Nonline-of-sight error mitigation in mobile location," *IEEE Trans. on Wireless Communication*, Vol. 4, 560–572, Mar. 2005.
28. Urrela, A., J. Sala, and J. Riba, "Average performance analysis of circular and hyperbolic geolocation," *IEEE Trans. on Vehicular Technology*, Vol. 55, 52–66, Jan. 2006.
29. Chen, P.-C., "A non-line-of-sight error mitigation algorithm in location estimation," *Proceedings of Wireless Communications and Networking Conference*, Vol. 1, 316–320, New Orleans, LA, USA, Sep. 1999.