A New Approach to Low Complexity UWB Indoor LOS Range Estimation

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Abstract—In this paper, the possibility of using UWB channel impulse response statistics, other than the TOA, for ranging applications, is investigated. Models for the total received signal power and for the first path power are proposed, based on an extensive UWB measurement campaign conducted in typical office environments. The use of the models is twofold: to obtain a best linear unbiased estimation of the distance and to identify the environment in which the transmitter and receiver are operating. Finally, the bandwidth dependency of the proposed approach is discussed and compared with that of the signal strength method, and a possible low complexity hardware implementation is suggested. The described strategy does not need synchronization between the system nodes, and only modest sampling rates are required. At the same time, the achieved standard deviation of the range error is 0.40 m, about 2.5 times less than obtained with the classical signal strength estimation.

I. INTRODUCTION

Recently, indoor positioning is attracting considerable attention from both research and industry. However, in indoor environments, the traditional services provided by e.g. the GPS are usually not available, unreliable or inaccurate [1]. For this reason, new solutions need to be developed.

Ultra-wideband (UWB) technology is considered as an ideal candidate to provide positioning information in these environments, due to its unique characteristics. In fact, it is well known that algorithms based on the measurement of Time of Arrival (TOA) or Time Difference of Arrival (TDOA) are able to reach centimeter level accuracy, at least in Line of Sight (LOS) propagation, when very large bandwidths are used [2]-[5]. On the other hand, this approach appears particularly demanding, and in a real positioning system the effective accuracy is limited by the hardware requirements of this solution. In particular, very high sampling rates and synchronization at sub-nanosecond level between the stations are needed. These requirements make the system expensive.

To avoid the complexity of TOA based solutions, UWB ranging based on Received Signal Strength (RSS) estimation has been investigated as a low complexity and low cost alternative [5], [6]. UWB signals show much smaller fading compared to narrowband signals due to their high time resolution; for this reason, this method indirectly exploits the unique feature of UWB: the very large bandwidth. However, the accuracy, even in LOS propagation, is limited to a few meters, and decreases for larger distances.

The purpose of this paper is to investigate the possibility of using statistics of the UWB channel other than TOA for range estimation, thus avoiding the problem of costly synchronization between the system nodes, but with improved accuracy compared to RSS. Statistical models for the total power of the received signal and for the power of the first path of the channel impulse response are proposed, based on an extensive UWB measurement campaign conducted in typical office environments. While the characterization of the received total power statistic has been widely documented in literature [7], only recently the authors in [8] started to analyze the first path power statistic. However, the possibility of using this statistic directly for the range estimation and solutions to estimate it with a low complexity receiver implementation, still have not been investigated. The models proposed in this paper are specified for each different environment of interest; in this way, it is possible to significantly reduce the variation of these statistics from their fit and much more accurate results can be obtained, compared to the case in which a global model is used. The same characterization of the proposed statistics is also used to identify the correct environment in which the transmitter and receiver are placed.

This paper is organized as follows. Section II describes the system setup, the measurement locations and the signal processing. In Section III, the measurement results and modeling are given. In Section IV, the proposed model is employed for the range estimation using a Best Linear Unbiased Estimator (BLUE) [9] of the distance. Section V shows how the knowledge of the model of the described statistics can be used to identify the environment in which the transmitter and receiver are placed. Section VI focuses on some implementation issues. First, the impact of the used bandwidth on the performance of the proposed approach is analyzed and compared to the case in which the classical RSS estimation is directly applied to the global set of data. Second, a possible low complexity hardware implementation of the proposed strategy is suggested, and the achieved performance is evaluated. Finally, in Section VII concluding remarks are provided.

II. SYSTEM SETUP, LOCATIONS AND DATA ANALYSIS

The CIR measurements were collected using a time domain technique. Details on the system setup can be found in [10]. The measurements were carried out in the EEMCS building of Delft University of Technology in LOS propagation using vertically polarized, omni-directional biconical antennas placed 1.5 m above the floor, and cover the bandwidth between 3.1 and 10.6 GHz allowed by the FCC for UWB radio transmissions. The walls in the building are made of concrete or brick and the floors of reinforced concrete. The distances between the transmitter and the receiver are between 2 and 11 m. The environments in which the measurements have been performed are: a laboratory room,
TABLE I
CHANNEL PARAMETERS FOR THE DIFFERENT ENVIRONMENTS

<table>
<thead>
<tr>
<th>Environment</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_{TP}$</td>
<td>1.31</td>
<td>1.52</td>
<td>1.22</td>
<td>1.60</td>
<td>1.21</td>
</tr>
<tr>
<td>$\sigma_{S,TP}$ [dB]</td>
<td>0.56</td>
<td>0.68</td>
<td>0.54</td>
<td>0.57</td>
<td>0.53</td>
</tr>
<tr>
<td>$n_{FP}$</td>
<td>1.79</td>
<td>1.91</td>
<td>1.90</td>
<td>1.88</td>
<td>1.85</td>
</tr>
<tr>
<td>$\sigma_{S,FP}$ [dB]</td>
<td>0.61</td>
<td>0.60</td>
<td>0.52</td>
<td>0.61</td>
<td>0.15</td>
</tr>
</tbody>
</table>

a corridor, an office, a corridor to office and a meeting room. These represent different propagation scenarios and allow to cover a large area of typical heterogeneous office environments. For easiness of notation, the environments are named: 1, 2, 3, 4, and 5, respectively. The measurements have been distributed between the minimum and maximum distance, to allow distance dependency modeling of the analyzed statistics. A total of about 400 measurements, each corresponding to different transmitter and receiver positions, has been collected.

The CIR $h(t)$ is estimated by deconvolving the received signal in the frequency domain using the inverse filtering technique. The spectrum of the received signal is divided by the one of the reference signal, measured at a distance of one meter, in the absence of reflections. In this way, it is possible to take into account the transmit and receive antenna transfer functions and the characteristics of the other system components. The division is done only for the frequency band of interest; the rest of the spectrum is filled with zeros. To reduce the leakage problem when transforming the signal back to the time domain, a Hamming window, which provides side-lobes less than -43 dB, is used.

III. MEASUREMENT RESULTS AND MODELING

A. Path-loss for the total signal power

The total power (TP) in the received signal decreases with the distance $d$ between the transmitter and the receiver, according to the law: $1/d^{n_{TP}}$, where $n_{TP}$ is the path-loss exponent. Using the log-normal fading assumption results in:

$$P_{TP}(d) = P_{0,TP} - 10n_{TP}\log_{10}\frac{d}{d_0} + S_{TP}$$

(1)

where $P_{TP}(d)$ is the power received at distance $d$, $d_0$ is the reference distance, $P_{0,TP}$ is the average measured power at the reference distance and $S_{TP}$ is a zero mean Gaussian distributed random variable in dB with standard deviation $\sigma_{S,TP}$.

B. Path-loss for the first path power

The first path (FP) of the CIR is defined here as the first local maximum of the envelope of the received signal, with amplitude within 25 dB from the strongest peak. By analyzing the measured data, it is found that also the first path power can be modeled with a linear decrease on a logarithmic scale of the distance:

$$P_{FP}(d) = P_{0,FP} - 10n_{FP}\log_{10}\frac{d}{d_0} + S_{FP}$$

(2)

with notations similar to those previously introduced. $S_{FP}$ has been modeled with a zero mean Gaussian distributed random variable in dB with standard deviation $\sigma_{S,FP}$. Table I summarizes the introduced parameters for the described environments.

IV. RANGE ESTIMATION

In this section, a BLUE [9] of the distance, combining in an optimal way the ranging results obtained using the total power and first path power statistics, is proposed. It is assumed that the environment (1.5) in which the transmitter and receiver are placed is known. This hypothesis will be removed in the next section. In the following, all the statistics are referred to the considered environment.

The range estimation using the total signal power is performed in the following way:

$$\hat{d}_{TP} = d_0 10^{\frac{P_{0,TP}-P_{TP}(d)}{10\sigma_{S,TP}}} = de^{-\frac{S_{TP}\ln 10}{10\sigma_{S,TP}}}$$

(3)

which is a log-normal random variable with mean and variance:

$$\mu_{\hat{d}_{TP}} = de^{-\frac{\sigma_{S,TP}\ln 10}{10\sqrt{2\pi\sigma_{S,TP}}}}$$

(4)

$$\sigma^2_{\hat{d}_{TP}} = d^2 e^{\left(-\frac{\sigma_{S,TP}\ln 10}{10\sqrt{2\pi\sigma_{S,TP}}}ight)^2} (e^{-\frac{\sigma_{S,TP}\ln 10}{10\sqrt{2\pi\sigma_{S,TP}}}} - 1)$$

(5)

In a similar way, for the range estimation using the first path power:

$$\hat{d}_{FP} = d_0 10^{\frac{P_{0,FP}-P_{FP}(d)}{10\sigma_{S,FP}}} = de^{-\frac{S_{FP}\ln 10}{10\sigma_{S,FP}}}$$

(6)

which is again a log-normal random variable with:

$$\mu_{\hat{d}_{FP}} = de^{-\frac{\sigma_{S,FP}\ln 10}{10\sqrt{2\pi\sigma_{S,FP}}}}$$

(7)

$$\sigma^2_{\hat{d}_{FP}} = d^2 e^{\left(-\frac{\sigma_{S,FP}\ln 10}{10\sqrt{2\pi\sigma_{S,FP}}}ight)^2} (e^{-\frac{\sigma_{S,FP}\ln 10}{10\sqrt{2\pi\sigma_{S,FP}}}} - 1)$$

(8)

For the calculation of the BLUE of the distance, there are two problems: first, the two introduced estimators are biased; second, the variance depends on the true distance which is unknown. To solve the first problem, the distance estimated with the two methods is normalized to obtain an unbiased estimation. Defining $\hat{d}_n$ as the vector of the normalized estimated distances, results:

$$\hat{d}_n = (\hat{d}_{TP}, \hat{d}_{FP}) \ast$$

(9)

$$\left( e^{-\left(-\frac{\sigma_{S,TP}\ln 10}{10\sqrt{2\pi\sigma_{S,TP}}}ight)^2} \right)$$

$$\left( e^{-\left(-\frac{\sigma_{S,FP}\ln 10}{10\sqrt{2\pi\sigma_{S,FP}}}ight)^2} \right)$$

where the operation $\ast$ represents the element by element matrix product. For the second point, it is worth to notice that the distance dependency of $\sigma^2_{\hat{d}_{TP}}$ and $\sigma^2_{\hat{d}_{FP}}$ results in both the cases in a multiplicative term $d^2$. The variance matrix $Q_{dd}$ can then be expressed as:

$$Q_{dd} = d^2 \cdot Q_{dd,0}$$

(10)

with $Q_{dd,0}$ independent of $d$ and defined as:

$$Q_{dd,0} = \left( \frac{\sigma^2_{\hat{d}_{TP}}}{\rho_{TP,FP}\rho_{S,TP}\rho_{S,FP}} \right)$$

(11)

$$\left( \frac{\rho_{TP,FP}\rho_{S,TP}\rho_{S,FP}}{\sigma^2_{\hat{d}_{FP}}} \right)$$

In this way, $\sigma^2_{\hat{d}_{TP}} = e^{-\left(-\frac{\sigma_{S,TP}\ln 10}{10\sqrt{2\pi\sigma_{S,TP}}}ight)^2} - 1$ and $\sigma^2_{\hat{d}_{FP}} = e^{-\left(-\frac{\sigma_{S,FP}\ln 10}{10\sqrt{2\pi\sigma_{S,FP}}}ight)^2} - 1$ (these expressions have been obtained by comparing (5) and (8) with (9)-(11)) can be calculated from the values of Table I. $\rho_{TP,FP}$ is defined as the correlation coefficient between the normalized range error obtained with total power and first path power, and it has been determined experimentally. Its value for the environments 1..5 is: 0.54, 0.66, 0.36, 0.92 and 0.51 respectively. The BLUE of the distance results in:

$$\hat{d}_{BLUE} = (A^T W_{BLUE} A)^{-1} A^T W_{BLUE} d_n =$$

(12)
\[(A^T Q_{dd,0}^{-1} A)^{-1} A^T Q_{dd,0}^{-1} d_n\]

where \(A = (1 \ 1)^T\) and \(W_{B L U E} = Q_{dd0}^{-1}\) is the BLUE weight matrix; the last equation in (12) is obtained by using (10) and observing that a multiplicative factor in the variance matrix has no impact on the BLUE.

Table II shows the standard deviation of the range errors for each single method and for the BLUE. It can be seen that the

<table>
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<tr>
<th>Environment</th>
<th>1</th>
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</tr>
</thead>
<tbody>
<tr>
<td>(\sigma_{d_{\text{RF}}} ) [m]</td>
<td>0.64</td>
<td>0.79</td>
<td>0.71</td>
<td>0.47</td>
<td>0.53</td>
</tr>
<tr>
<td>(\sigma_{d_{\text{RF}}} ) [m]</td>
<td>0.50</td>
<td>0.56</td>
<td>0.26</td>
<td>0.42</td>
<td>0.09</td>
</tr>
<tr>
<td>(\sigma_{d_{\text{BLUE}}} ) [m]</td>
<td>0.45</td>
<td>0.55</td>
<td>0.26</td>
<td>0.42</td>
<td>0.08</td>
</tr>
</tbody>
</table>

range estimation based on the first path power gives better results than that based on the total power. \(\sigma_{d_{\text{RF}}} \) varies between 0.09 m for environment 5 due to the very small \(\sigma_{d_{\text{RF}}} \) and 0.56 m for environment 2. Combining the two methods in the BLUE allows, at least for some environments, to further improve the range accuracy, compared to using only the first path power; the relatively small improvement is due to the much better accuracy provided by the first path power compared to the total signal power, and to the correlation in the range error obtained with the two methods.

The global standard deviation of the range error obtained with the BLUE results in \(\sigma_{d_{\text{BLUE}}} = 0.38 \) m, and it is smaller than 0.67 m with 90% probability. For comparison, it is worth to underline that the standard deviation of the range error obtained with the classical RSS estimation directly applied to the global set of measurements results in \(\sigma_{d_{\text{RSS}}} = 1.01 \) m, which is more than 2.5 times larger. On the other hand, the use of the first path power only, applied to the global set of data (without the distinction between the different environments), achieves a standard deviation of the range error of 0.49 m, about half of that obtained with the total signal power. In this case, the only a priori knowledge required is the first path power path loss exponent of the global set of data, which in our set of measurements is 1.87.

For this reason, this last approach appears an appealing solution for a low cost positioning system which requires very modest a priori channel information. The better performance of the first path power statistic, compared to the total signal power, is due to the larger value of its path loss exponent, and to the smaller variation of this statistic among the different environments.

V. Environment Identification

In the previous section, it has been assumed that the environment in which the transmitter and receiver are located, is known. However, this is usually not the case in a real positioning system, and even the knowledge of the transmitter ID, is generally not enough to univocally identify the environment.

In this section, we show how the parameters introduced in Section III can be used to identify the environment in which the transmitter and receiver are located. In this way, the only a priori information required by the described approach is the accurate modeling of the previously presented statistics for the environments of interest.

Considering the following test statistic:

\[r^{(e)} = \hat{d}_{TP}^{(e)} - \hat{d}_{FP}^{(e)}\]

where \(r^{(e)}\) indicates that the quantities are referred to the generic environment \(e\) (in our case \(e = 1..5\)). The decision approach is the following:

- The different \(r^{(e)}\) are computed for the different possible environments of interest.
- The environment \(e\) is chosen as:

\[
\arg\min_{\{e\}} \left\{ |r^{(e)}| \right\}
\]

where \(|.|\) represents the absolute value operation. The intuitive explanation of this decision strategy is the following: if we are in the right environment, (and thus we use the correct channel parameters), \(|r^{(e)}|\) is small, since both \(\hat{d}_{TP}^{(e)}\) and \(\hat{d}_{FP}^{(e)}\) are close to the true distance; if we are in the wrong environment, it is likely that \(\hat{d}_{TP}^{(e)}\) and \(\hat{d}_{FP}^{(e)}\) give significantly different values and \(|r^{(e)}|\) is large.

Denoting with \(\hat{d}_{c}\) the estimated distance (with the total power or with the first path power) in the case of correct choice of the environment, and with \(\hat{d}_{e}\) the same estimated distance in the case of incorrect choice of the environment:

\[
\hat{d}_{c} = d_{0} 10^{-\frac{\Delta_{TP} - P(d)}{10 \log_{10} d/d_{0} + S}}
\]

\[
\hat{d}_{e} = d_{0} 10^{-\frac{\Delta_{FP} - P(d)}{10 \log_{10} d/d_{0} + S}}
\]

Using (13) and (15), after some calculation, denoting with \(r\) the test statistic under the case of correct choice of the environment (and omitting the apex \((e)\)), we have:

\[
r_{c} = \frac{S_{TP}}{10 n_{TP}} - \frac{S_{FP}}{10 n_{FP}}\ln 10
\]

This expression has been obtained using a first order approximation around zero for the exponential terms (for this statistic this is a good approximation, since the arguments of the exponential terms are usually of the order of 0.1). In a similar way, using (13) and (16), denoting with \(r_{i}\) the test statistic under the case of incorrect choice of the environment, results in:

\[
r_{i} = \frac{S_{TP}}{10 n_{TP}} - \frac{S_{FP}}{10 n_{FP}}\ln 10
\]

Under the described approximations, \(r_{c}\) and \(r_{i}\) are two correlated Gaussian random variables, the first with zero mean, the second with a mean different from zero given by:

\[
\Delta n_{TP}/n_{TP} - \Delta n_{FP}/n_{FP}
\]

where:

- \(\Delta n_{TP} = n_{TP} - n_{FP}, \Delta n_{FP} = n_{FP} - n_{TP}\). Also this expression has been obtained using a first order approximation around zero for the exponential terms (for the purpose of this analysis, also this one is a good approximation since the arguments of the exponential terms are usually of the order of 0.3).
\( \Delta n_{FP}/n_{FP}' \log_{10} \frac{d}{d_0} \ln 10 \) (normalizing \( r |c \) and \( r |i \) by a factor \( d \) which is not relevant for the decision strategy). For this reason, with the proposed approach, it is likely to choose the test statistic for the correct environment, which corresponds to the zero mean random variable \( r |c \). The absolute value of the mean increases with the distance, so the decision strategy becomes more robust for larger distances.

To get further insight in the decision strategy proposed in (14), in the following we will analyze a simple example in which only two environments, named (1) and (2), are considered. The conditions under which this decision strategy is optimum are derived, and a refinement to the approach, useful in the practical situation in which some of these conditions are not satisfied, is suggested. The hypotheses in which we are in the environment (1) and (2) are denoted with \( H_1 \) and \( H_2 \), respectively.

From the variance propagation law applied to the system of equations (17) and (18), we find: \( \rho_{r |c}, r |i} \approx 1 \) for all the considered environments. Using this consideration, and observing that given two generic random variables \( X \) and \( Y \), the first with zero mean, the second with a mean different from zero, and with \( \rho_{X,Y} = 1 \), we can write: \( Y = aX + b \), a different way to represent \( r |c \) and \( r |i \) is then:

\[
\Delta r = (r \,(1))^2 - (r \,(2))^2
\]  
where the parameters \( v \), \( u \) and \( \sigma \) can be obtained for comparison with (17) and (18). Under the two hypotheses \( H_1 \) and \( H_2 \), (19) becomes:

\[
H_1: \quad (r \,(1))^2 \approx N(0, \sigma_1^2); \quad (r \,(2))^2 \approx u \,(1) + u \,(2) \quad (20)
\]

\[
H_2: \quad (r \,(2))^2 \approx N(0, \sigma_2^2); \quad (r \,(1))^2 \approx u \,(2)^2 + u \,(2)^2 \quad (21)
\]

where \( u \,(i) \) is the order of magnitude of \( \sigma \) for \( i = 1, 2 \), can be obtained with (17) and (18), referred to the environment \( i \).

We introduce now the following quantity:

\[
\Delta r = (r \,(1))^2 - (r \,(2))^2
\]  
Using (20) and (21), under the two hypotheses, \( \Delta r \) can be expressed as:

\[
\Delta r \approx \begin{cases} 
(r \,(1))^2 - (u \,(1))^2 & |H_1| \\
-(r \,(2))^2 + (u \,(2))^2) & |H_2|
\end{cases}
\]

Observing that \( |u \,(i)| \) is of the order of magnitude of \( \sigma_i \) and using \( v \,(i) \approx 1 \), (23) is obtained in the case of perfect knowledge of the environment. The estimation performance is not significantly affected, since the right environment is confused with one with similar parameters. But this means that \( \Delta n_{FP} \) should be significantly different from zero and at the same time \( \Delta n_{FP} \) should be larger than it, since \( n_{FP} > n_{TP} \); however, this does not happen in our measurements (in general the variation of \( n_{FP} \) is very modest or smaller than of \( n_{TP} \)). On the contrary, if \( \Delta n_{TP} \approx \Delta n_{FP} \approx 0 \) but \( \Delta n_{FP} \) and \( \Delta n_{TP} \) are both close to zero, the test is likely to be wrong, but the range estimation performance is not significantly affected, since the right environment is confused with one with similar parameters.

With the \( \alpha(e) \) determined by simulation, the standard deviation of the range error is about 0.40 m, which is very close to the value obtained in the case of perfect knowledge of the environment. The failure ratio of the proposed test is relatively high (about 23%), but the accuracy is not affected significantly. This is due to the incorrect choice of environments with rather similar parameters. In case in which the parameters of the channel are different, on the contrary, the test is able to correctly identify the environment. Fig. 1 shows the BLUE range error obtained with the a priori knowledge of the environment and with the proposed decision approach for comparison.

<table>
<thead>
<tr>
<th>Distance [m]</th>
<th>Error [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
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<td>5</td>
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<tr>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>0</td>
</tr>
</tbody>
</table>

| Decision approach − correct decision |
| Decision approach − incorrect decision |

Fig. 1. BLUE range error vs. \( d \) obtained with the a priori knowledge of the environment and with the proposed decision approach.

Under the introduced approximations, the critical value of the test does not depend on the distance (which is unknown, and we cannot correctly estimate it, since we still do not have knowledge of the environment). If we remove some of the last simplifying hypotheses it is not trivial anymore to derive the optimum decision rule, since we have, under the two hypotheses, two random variables with different standard deviations and means which depend on the unknown distance.

As explained, the last introduced approximation \( \sigma_1 \approx \sigma_2 \) does not hold in our measurements, and for this reason the test proposed in (14) is not optimum anymore. For this reason, the decision strategy has been modified as: \( \text{argmin}_{e} \{ \alpha(e) | r \,(i) \} \), where \( \alpha(e) \) are fixed weight coefficients determined by simulation from the collected data, to minimize the standard deviation of the global range error.
VI. IMPLEMENTATION ISSUES

A. Bandwidth dependency

In this section, the performance of the proposed strategy, depending on the used bandwidth, is analyzed, and a model for the standard deviation of the achieved range error is derived and compared with that obtained with the classical RSS.

The spectrum of the received signal is filtered with a rectangular window centered in $f_c = (3.1 + 10.6)/2$ GHz = 6.85 GHz, and with bandwidth $B$ varying between 0.5 GHz and 7.5 GHz, increased in steps of 0.5 GHz. Table III shows the parameters introduced in Section III for different bandwidths. For space reason, only the results for $B = 0.5$ GHz and $B = 3$ GHz are shown. These results can be compared with those of Table I referred to the full bandwidth of 7.5 GHz.

It can be seen that both $\sigma_{S,T,P}$ and $\sigma_{S,F,P}$ significantly increase for smaller $B$; the increase is more pronounced for $\sigma_{S,F,P}$. For this reason, when smaller $B$ are used, the BLUE allows to noticeably improve the performance of the range estimation compared not only to the case in which only the total power is used, but also to the case in which only the first path power is used (this does not happen for large $B$), as shown in the same Table III.

Fig. 2 shows the standard deviation of the error obtained with the BLUE of the distance as a function of $B$, with the a priori knowledge of the environment. It can be seen that $\sigma_{d,\text{BLUE}}$ increases from 0.38 m for $B = 7.5$ GHz up to 1.80 m for $B = 0.5$ GHz. The same figure also presents the standard deviation of the range error obtained without the a priori knowledge of the environment and using the approach presented in Section V. For large bandwidths, the increase of $\sigma_{d,\text{BLUE}}$ is limited to not more than 2 cm. On the contrary, for bandwidths smaller than 3 GHz, the use of the proposed environment identification strategy achieves slightly smaller range errors than the a priori knowledge of the environment. We think that this point deserves further analysis. For comparison, the same figure shows also the standard deviation of the range error obtained with the classical RSS directly applied to the global set of measurements. The proposed solution always outperforms the RSS. However the improvements are much more evident for larger $B$, for two reasons. First, in this case, a more consistent part of the error in the classical RSS is represented by the combining of heterogeneous environments with different path-loss exponents. This problem is solved in the proposed approach by distinguishing between the different environments. Second, as underlined, by decreasing $B$, the increase of $\sigma_{S,F,P}$ is more consistent than of $\sigma_{S,T,P}$ and the use of also the model for the first path power allows to improve less the accuracy of the range estimation obtained using only the total power.

By analyzing the obtained results, the standard deviation of the range error as a function of $B$ has been modeled as:

$$\sigma_d = ae^{-\frac{g}{B} + c}$$  \hspace{1cm} (25)

The values of $a$, $b$, $c$, and $g$ have been determined to minimize the mean square error from the measured data and are reported in Table IV. The fits to the data are also shown in Fig. 2.

B. Low complexity hardware implementation

The analysis of the previous sections has been proposed based on UWB CIR measurements in typical LOS indoor office environments. In these scenarios, the strongest path is usually the first one, due to the scarceness of metallic reflectors and the good penetration capabilities of UWB signals for the most common building materials.

Capitalizing on this observation, the proposed receiver circuit implementation, shown in Fig. 3, assumes that the first path is always the strongest one. The impact of this assumption will be evaluated in the following. The upper part of the circuit estimates $P_{T,P}$, the lower part $P_{F,P}$. This last circuit is a classic envelope detector composed of a diode followed by an RC circuit. However, the values of $R$ and $C$ are set to affect the output signal with the "diagonal clipping" phenomenon [11]. The time constant of the circuit $\tau = RC$ in fact is chosen very large; in this way, the output, instead of following the envelope of the signal, tends to decrease from its largest value very slowly and,
for the purpose of estimating the peak amplitude, can be sampled with a relatively low sampling rate. The principle of operation of the described solution is shown in Fig. 4. $P_{FP}$ is estimated as:

$$P_{FP} \approx 10 \log_{10} \left( \max \{ x[i] / (1 - T/(2\tau)) \} \right) \quad (26)$$

where $x[i] = x(it)$ are the samples collected in one transmission, $x(t)$ is the signal at the output of the envelope detector and $T$ is the sampling period. In fact, $x(t)$ can be approximated around the peak with its derivative $1 - (t - t_0)/\tau$ (normalized for easiness of notation to the peak amplitude; $t_0$ is the (unknown) TOA of the peak). $\max \{ x[i] \}$ is then a uniformly distributed random variable in the interval $[1 - T/\tau, 1]$. By dividing $x[i]$ by $1 - T/(2\tau)$, and using a first order approximation, $\max \{ x[i] / (1 - T/(2\tau)) \}$ is uniformly distributed around the correct mean $U \{ 1 - T/(2\tau), 1 + T/(2\tau) \}$ and its variance due to the sampling quantization is: $(T/\tau)^2/12$. For example, by choosing: $T = 20$ ns (which means a sampling rate of 50 MHz) and $\tau = 500$ ns, the standard deviation of the quantization error introduced by the proposed solution is about 0.1 dB, which is very small (however it is possible to obtain different values with a different choice of $T$ and $\tau$). The final standard deviation of the range error achieved by this approach and with the proposed set of parameters differs from the one reported in Fig. 2 by less than 3% for all $B$, and for this reason the analysis proposed in the previous section can be applied to the implementation hereby described.

VII. CONCLUSION

In this paper, a new approach to UWB ranging in indoor LOS environments has been proposed. First, based on an extensive UWB measurement campaign conducted in typical office scenarios, models for the total signal power and for the first path power have been presented. The BLUE of the distance is analyzed, using the models developed, and exploiting the information of the correlation between the errors in the range estimation provided by each method. By distinguishing between the different environments of interest, it is possible to considerably reduce the variation of the described statistics from the fit, and to obtain a very accurate range estimation. In Section V, the described statistics have been used for determining the environment in which the transmitter and receiver are placed. The final standard deviation of the range error is 0.40 m, significantly smaller than obtained by applying the traditional RSS on the global set of measurements (which results in $\sigma_{d_{\text{RSS}}} = 1.01$ m). Finally, in Section VI some implementation issues are discussed. First, a model for the bandwidth dependency of the standard deviation of the range error obtained with the proposed solution is presented and compared with that of the classical RSS. Then, a possible low complexity hardware implementation of the described strategy is proposed. This solution allows to solve the two main hardware limitations usually experienced by TOA based solutions: the very high sampling rates and the sub-nanosecond synchronization among the stations. To avoid the a priori knowledge of the channel statistics of the different environments, required by the approach presented in Section IV and V, the use of the first path power only, directly applied to the global set of data, represents an interesting alternative. The described approach can be directly applied in a real environment, combined with a LOS/NLOS detection algorithm [12] which allows to select only the LOS measurements.

REFERENCES