A Preliminary Investigation on Angular Parameters Estimation in a Simplified IR-UWB Indoor Multipath Scenario

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Abstract—This paper presents an algorithm that interprets the waveforms associated with received multipath components in order to estimate their Direction of Arrival (DoA), Direction of Departure (DoD) and Incident Angle to the Indoor Surface (IAIS) in the context of Impulse Radio - Ultra Wide Band (IR-UWB) communications. The proposed solution combines a deterministic description of the filtering effects of antennas and materials with a simple statistical model for IAIS. Iteratively, a set of jointly estimated path parameters is chosen according to the cross-correlation values obtained with currently resolved paths and predicted waveforms. Following an estimation tree approach, impossible sets are progressively discarded. An Estimation Quality Indicator is defined, in order to handle aberrant configurations made up of five single-bounce estimated paths. We show here that the IR-UWB transmission technology, which benefits from fine resolution capabilities, looks particularly suitable to the discussed algorithm. Assuming known walls material, simulation results are provided to illustrate the performance of such a technique in a simplified peer-to-peer multipath scenario. The proposed solution discloses new perspectives for context-awareness through classical communication links.

Index Terms—Antenna, Context-Awareness, Direction of Arrival, Direction of Departure, Electromagnetic Interaction, Impulse Radio, Indoor Environments, Reflection, Ultra Wide Band

I. INTRODUCTION

Indoor applications such as monitoring, self-configurable and efficient wireless communication systems, house automation and home entertainment will probably meet market needs soon. Consequently, environment awareness (e.g. presence, distance, orientation, nature of surrounding walls or obstructing obstacles) is more and more required for radio devices.

Besides, the flexibility and the intrinsic properties of the Impulse Radio - Ultra Wide Band (IR-UWB) technology (e.g. low power consumption, scalability, advanced ad hoc networking, precise range measurements, etc.) have been exploited for wireless communications and radiolocation (e.g. [1]). Relying on the fine temporal resolution capability of UWB pulses, several studies have even been started in the field of environment characterisation, such as Radio Frequency (RF) indoor sensing and imaging based on UWB radar (e.g. [2], [3]), geo-regioning (e.g. [4]) and indoor mapping (e.g. [5]). Finally, in [6] and [7], the joint estimation of directions is performed using techniques based on UWB antenna arrays.

The work [8] presented a simple algorithm which jointly estimates the Direction of Arrival (DoA), Direction of Departure (DoD) and material typecasting for temporally well-isolated UWB pulses making the assumption of a free-space propagation. In both of previous works, estimates are provided using a Single Input Single Output (SISO) communication.

The paper presented in this paper gets rid of some assumptions of [8] (e.g. temporal path isolation, square room geometry) and proposes a new iterative algorithm integrating the multipath nature of indoor IR-UWB communications from a novel statistical point of view. The algorithm enables classical SISO digital communications while inferring angular parameters (e.g. DoA, DoD, incident angles to surfaces) by interpreting significant multipath components on the receiver side (i.e. simple-bounce reflected and direct paths). The proposed technique relies on the capability of predicting site-specific filtering electromagnetic interactions with environment, as described for deterministic tools (e.g. [10]-[12]) and on the preliminary knowledge of antennas behaviour (e.g. through prior measurements or simulations).

The paper is organised as follows. In Section II, the effects of the most significant electromagnetic interactions are briefly presented. Section III introduces the received signal model, while Section IV illustrates the parameters of a simplified indoor scenario. Then, Section V introduces some concepts about the Incident Angles to Indoor Surfaces (IAIS), while Section VI proposes a tree approach for the joint estimation of angular parameters in multipath scenarios. Subsequently, Section VII discusses preliminary results in a chosen 2D scenario. Finally, Section VIII concludes the paper.

II. WIDE-SENSE UWB INDOOR CHANNEL

In [13], [14], it has been shown that UWB antennas provide shape diversity to the pulse, depending on transmitting and receiving directions, respectively $s_{tx}$ and $s_{ry}$. As admissible radiation directions are subject to indoor environment geometry, the wide-sense UWB propagation channel can be considered as including UWB antennas filtering. In a typical indoor environment, transmission and reflection phenomena mainly affect radiated waveforms. Actually, as described in [15], the UWB pulse shape observed after a reflection on or a transmission through a slab (e.g. wall, window, door) appears to be deformed in comparison with the incident pulse. This deformation mostly depends on the thickness of the slab, which causes multiple internal reflections interfering with the incident pulse, as well as on the complex dielectric permittivity and on the angle of incidence $\theta_i$ to the slab.
III. MULTIPATH SIGNAL MODEL

In the context of noised IR-UWB indoor communications, the received signal $\rho(t)$ is generally described as a sum of paths, resulting from $N_{\text{int}}$ electromagnetic interactions:

$$\rho(t) = \sum_{n=1}^{N_{\text{int}}} r_n(t - \tau_n) + \eta(t)$$  \hspace{1cm} (1)

where $r_n(t)$ is the $n$-th filtered received path, $\eta(t)$ is the filtered noise affecting the link and $\tau_n$ is the $n$-th path delay.

As the description of electromagnetic phenomena appears simpler in the frequency domain, it is worth transposing the generic received path $r_n(t)$ into the latter domain. In particular, it has been shown in [10] that, after discarding deliberately the time shift due to the unknown distance travelled by the signal, the tension $R(f)$ corresponding to the generic received path at the output of the receiving antenna can be written as follows:

$$R(f) = H_{e,\text{rx}}(f, \varphi_x) G_{\text{rx}}(f) S(f)$$  \hspace{1cm} (2)

where $S(f)$ is the Fourier Transform of the unitary signal $s(t)$ feeding the transmitting antenna, $H_{e,\text{rx}}(f, \varphi_x)$ and $G_{\text{rx}}(f)$ can be described as follows:

$$H_{e,\text{rx}}(f, \varphi_x) = -j \frac{\lambda}{4\pi} \sqrt{\epsilon} \begin{bmatrix} E_{\varphi}(f, \varphi_x) \\ E_{\varphi'}(f, \varphi_x) \end{bmatrix}$$

and

$$G_{\text{rx}}(f) = \sqrt{\epsilon} \begin{bmatrix} E_{\varphi}(f) \\ E_{\varphi'}(f) \end{bmatrix}$$

where $\lambda$ is the wavelength corresponding to frequency $f$, $\frac{\lambda}{4\pi}$ accounts for the integration at the receiver side, $\sqrt{\epsilon}$ is the maximum antenna gain, $E_{\varphi}$ terms are the components of the electric field vector to be radiated. The former vectors account for the frequency domain behaviour of receiving and transmitting antennas respectively in radiating directions $\varphi_x$ and $\varphi_x'$. Note that, without loss of generality, this model implies that the same antenna is used on both transmitting and receiving sides. Finally,

$$C_{\text{int}}(f) = \begin{bmatrix} C_{\varphi,\varphi'}(f) \\ C_{\varphi',\varphi}(f) \\ C_{\varphi,\varphi'}(f) \\ C_{\varphi',\varphi}(f) \end{bmatrix}$$  \hspace{1cm} (3)

is the path channel matrix, accounting for electromagnetic phenomena affecting the path (i.e. path loss, reflections, refractions, etc.) over each field component. $C_{\text{int}}(f)$ is particular for each of the $N_{\text{int}}$ received paths, as a function of the suffered interactions. Note that the channel matrix above supposes that cross-polarisation terms are negligible. In the following, the paths issued from multiple reflections and from other more complex interactions (e.g. refraction, diffraction) will be ignored for the sake of simplicity. Therefore, the considered multipath model involves up to four simple-bounce paths and a direct path (i.e. $N_{\text{int}} = 5$), which potentially overlap depending on the geometry of the scenario. Indeed, it generally makes sense considering that simple-bounce paths carry the most significant part of the received energy.

IV. SIMPLIFIED INDOOR SCENARIO

Let us define a simplified 2D indoor scenario as a rectangular room which walls are made up of one of the following materials: brick, wood, glass. Each material slab is assumed to have a known thickness (e.g. 7 cm for a brick wall). Therefore, referring to Figure 1, the largest room dimension is defined as $D_x$ and the other dimension as $D_y$.

As a peer-to-peer communication is simulated, a transmitter and a receiver are also shown, materialised in grey and dark grey spots respectively. The corresponding coordinates are two additional scenario parameters, respectively $(x_t, y_t)$ and $(x_r, y_r)$. As a 2D scenario is analysed, in the following DoA and DoD will be called more properly Angle of Arrival (AoA) and Angle of Departure (AoD) respectively.

V. INCIDENT ANGLES TO INDOOR SURFACES

A. Joint Probability Density Function

The previous work [8] gave a statistical model for an expected incident angle in a square room, assuming transmitter and receiver coordinates as uniform random variables. Nevertheless, in a rectangular room scenario, incident angles on the largest edges of the room (i.e. the two walls corresponding to length $D_x$) have a different Probability Density Function (PDF) from that of incident angles on the smallest edges of the room (i.e. the two walls corresponding to length $D_y$). In both PDFs, the ratio $R_D = \frac{D_x}{D_y}$ is the only geometric parameter involved. Therefore, the expectation can not be calculated any more and a new approach has to be applied. As the PDFs of incident angles are not used in the following, their analytical expressions will not be presented. As an illustration, the PDFs for three $R_D$ values can be found on Figure 2.

The new approach developed in this work is based on the joint PDF of the four Incident Angles to Indoor Surface (IAIS), namely $f_d(\theta_1, \theta_2, \theta_3, \theta_4)$, corresponding to the four simple-bounce interactions that can be observed in the simplified scenario described above. The joint PDF has been calculated assuming a uniform distribution of random transmitting and receiving coordinates in the room. Then, thanks to simple geometrical relationships, the analytical joint PDF can be written as follows:

$$f_d(\theta_1, \theta_2, \theta_3, \theta_4) =$$

$$\xi \gamma(\theta_1) \gamma(\theta_2) \gamma(\theta_3) \gamma(\theta_4) \tan \theta_1 \tan \theta_2 \tan \theta_3 \tan \theta_4 \left(\tan \theta_{1,2,3,4} \right)^2$$

if $(\theta_1, \theta_2, \theta_3, \theta_4) \in \mathcal{D}$, where $\gamma(\theta_{1,n}) = 1 + \tan^2(\theta_{1,n})$ and $\xi$ is a normalisation factor depending on the domain $\mathcal{D}$. Otherwise, $f_d(\theta_1, \theta_2, \theta_3, \theta_4)$ takes the null value. The equations enabling the analytical definition of $\mathcal{D}$ can be calculated starting from the constraint that transmitter and receiver abscissas and ordinates should be between 0 and respectively.
\[ R_D \tan \theta_{i,2} \tan \theta_{i,3} + R_D \tan \theta_{i,4} - \tan \theta_{i,1} \tan \theta_{i,2} + \tan \theta_{i,1} \tan \theta_{i,3} + \tan \theta_{i,1} \tan \theta_{i,4} > 0 \]

\[ R_D \tan \theta_{i,1} + R_D \tan \theta_{i,2} + \tan \theta_{i,3} + \tan \theta_{i,4} > 0 \]

\[ R_D \tan \theta_{i,1} - R_D \tan \theta_{i,2} + \tan \theta_{i,3} - \tan \theta_{i,4} > 0 \]

\[ R_D \tan \theta_{i,1} \tan \theta_{i,4} + \tan \theta_{i,2} \tan \theta_{i,3} - R_D \tan \theta_{i,1} \tan \theta_{i,2} + \tan \theta_{i,3} - R_D \tan \theta_{i,1} \tan \theta_{i,4} < 0 \]

\[ \xi = \int_D \frac{\gamma(\theta_1) \gamma(\theta_2) \gamma(\theta_3) \gamma(\theta_4)}{(\tan \theta_1 + \tan \theta_3)^3 (\tan \theta_2 + \tan \theta_4)^3} d\theta_1 d\theta_2 d\theta_3 d\theta_4 \]  

(C. Potential Probability Spaces)

Let us call Cluster Input Set (CIS) a set of estimated incident angle cluster labels, corresponding to a given scenario (i.e. \( \theta_{i,1}, \theta_{i,2}, \theta_{i,3}, \theta_{i,4} \)). Note that it is not possible to \textit{a priori} associate an element of CIS to an incident angle \( \theta_{i,n} \), as the algorithm does not know the mapping between resolved received paths and model labelling. Let us also note that each permutation of the elements of a CIS is associated with a particular probability, as \( f_{\theta_{i,n}} \) is not invariant over the permutations of \( \theta_{i,n} \). For instance, from (4) one can deduce that \( f_{\theta_{i,n}} \) is invariant over all the permutations of \( \theta_{i,1} \) with \( \theta_{i,3} \), but it is not invariant over all the permutations of \( \theta_{i,1} \) with \( \theta_{i,2} \). Therefore, each numerically sorted CIS can be linked to a space of probability, which will be called Potential Probability Space (PPS), made up of the probabilities associated with each possible permutation. The probabilities result from the integration of \( f_{\theta_{i,n}} \) over the corresponding cluster supports. In such a space it is always possible to find a maximum (i.e. maximal potential probability) and a minimum value (i.e. minimal potential probability).

VI. PROPOSED ESTIMATION APPROACH

A path-by-path approach is proposed, as for each resolved path a set of candidates to estimation is selected. Then, an estimation tree structure is provided, where the latter set is a layer and a chain of paths estimates is a branch in the tree. As a new path is considered, the tree depth grows by one more layer. In order to set up a new tree layer, two tasks are performed, namely the selection of candidates for the current detected path (i.e. among predicted waveforms) and the elimination of estimation branches leading to a null probability. The first task is mainly based on the cross-correlation between a portion of the received signal and predicted waveforms. The second task involves statistical constraints issued from simple geometrical considerations. As a matter of fact, IAIS account for room geometry, as their joint distribution depends on \( R_D \) and \( R_A \). Moreover, assuming a rectangular geometry, the quartet \( (\theta_{i,1}, \theta_{i,2}, \theta_{i,3}, \theta_{i,4}) \) must not take any value, as there will be some quartets incompatible with a rectangular geometry and a given ratio \( R_D \). Therefore, an approach involving joint IAIS probability is expected to slightly compensate for a degradation of the recognition capability provided by algorithms only based on cross-correlation (e.g. [8]) in noisy multipath scenarios. In order to improve paths detection, resolved paths are deleted progressively out of the received signal.

A. Synthesised Waveforms

As the generic received waveform depends on receiving and transmitting directions, a set of \( N_{dir} \) direction couples must be considered:

\[ \left\{ \left( \sum_{k=1}^{N_{dir}} \left( \sum_{d \in \text{dir}} \right) \right) \right\}_{k=1}^{N_{dir}} \]

Moreover, material filtering depends on the particular incident angle, so that synthesised waveforms depend on the incident
angle too. As a clustering method has been applied to variables $\theta_i$, each synthesised waveform will depend on the IAIS cluster label $l_i$. Subsequently, $\mathcal{C}(m,l_i)(f)$ corresponds to the path channel matrix (3) for a simple-bounce interaction with the $m$-th characterised material under an incident angle contained in the IAIS cluster $l_i$:

$$\mathcal{C}(m,l_i)(f) = \left[ \begin{array}{ccc} M_{g_{\gamma_i}}^{(m,l_i)}(f) & \varepsilon & M_{g_{\rho_i}}^{(m,l_i)}(f) \\ \varepsilon & \ddots & \varepsilon \\ M_{g_{\rho_i}}^{(m,l_i)}(f) & \varepsilon & M_{g_{\gamma_i}}^{(m,l_i)}(f) \end{array} \right]$$

(7)

where $\varepsilon$ is a negligible contribution of cross-polar components. Therefore, the generic synthesised waveform $R^{(m+l_i)}(f)$ is obtained by replacing matrix (7) into (2). The inverse Fourier transform operator $\mathcal{F}^{-1}[-\cdot]$ is then applied to the resulting signal. Finally, the time-domain signal is normalised in energy. In the following we will refer to $r^{(m,l_i)}(t)$ as the time-domain synthesised received waveform, issued from receiving and transmitting directions, respectively $\gamma_i$ and $\rho_i$, assuming a single-bounce reflection on the $m$-th characterised material and an incident angle contained in the $l_i$-th cluster of $\theta_i$.

B. Signal Cleaning with Rejection Windows

Referring to (1), in a typical indoor scenario, the observed times of arrival $\tau_n$ can be quite similar. Depending on the bandwidth of the communication system and on the employed antenna (i.e. the more different are in-band group delays, the higher is the waveform time spread), some overlaps can be observed. The benefits of a modified CLEAN algorithm based on cross-correlation for UWB indoor channel analysis are discussed in [17]. This algorithm enables deleting progressively detected paths out of the received signal. The detection is iteratively performed by calculating the energy of the signal to be cleaned (i.e. the received signal for the first iteration) over a sliding window. When a new energy maximum is detected while sweeping across the signal, a cross-correlation based CLEAN algorithm is applied to the corresponding time window. Then, the selected synthesised cleaning waveform, adequately delayed and scaled, is subtracted to the current signal. In addition to the discussed CLEAN algorithm, a rejection window is considered in order to prevent the algorithm from selecting a pick issued from a residue of a previous cleaning process as a new energy maximum. Therefore, the calculation of the energy will be performed on the product of the signal to be cleaned and a mask. When a path is detected in a time window, an interval on this time window is set to the null value in the mask, so that the selected interval is rejected for next iterations.

C. Estimation Tree

The previous work [9] showed that there is not a one-to-one correspondence between waveforms shapes and their parameters, even when the pulse energy is higher than noise power density by several dBs. Therefore, a strategy based on multiple choices will be employed, in order to select just a set of candidates for each resolved path in the received signal, deferring the final estimation to a further stage. Referring to [9], a Flex strategy with $N_c = 2$ is applied here. In this paper, $N_{\text{dispert}}$ corresponds to $N_c$ as cited above. In order to provide a benchmark for the proposed algorithm, let us consider an estimation method which will consider a fixed number $N_{\text{permant}} \times N_{\text{dispert}}$ of potential estimates for each resolved path. In the following this approach will be called Blind Algorithm (BA). If we just consider 4 simple-bounce received paths, the number of possible combinations is $(N_{\text{permant}} \times N_{\text{dispert}})^4$, showing an exponential growth as a function of the number of the received paths. Therefore, the following discussed algorithm has been designed to limit exponential complexity growth. First of all, it is useful to employ an estimation tree, where estimation candidates are nodes and a full-depth branch can be seen as an estimated configuration (i.e. for all the resolved paths). Besides, it is suitable not to have an a priori fixed number of incident angles for each material $N_{\text{permant}}$, as predicted received waveforms are not equally tolerant of noise (e.g. [9]). It is also expected that waveforms would not be equally tolerant of multipath overlap, as they show different temporal supports depending on the radiating directions (i.e. AoD and AoA) and on the suffered interaction. Therefore, the discussed algorithm tunes the value of $N_{\text{permant}}$ following a cross-correlation based criterion. The criterion tends to let survive more candidates when there is a high uncertainty in the candidate choice (i.e. when cross-correlation values are very similar). Consequently, the algorithm takes the maximum cross-correlation value (i.e. among the $N_{\text{dispert}} \times N_{\text{permant}}$ remarks), then normalises cross-correlation values with respect to the maximum and makes a choice following a selection threshold $\gamma$, so that estimates corresponding to normalised cross-correlation values higher than $\gamma$ will be kept as surviving candidates (i.e. by groups of $N_{\text{dispert}}$ candidates). Otherwise they will be discarded one and for all. Afterwards, surviving candidates are subject to an elimination criterion based on the maximal potential probability associated with each surviving branch, as defined in V-C. Therefore, if the current surviving branch is associated with a null maximal potential probability (i.e. current configuration is impossible in the chosen geometrical scenario), this branch is discarded one and for all. The selection criterion takes also into account that only the first received path can be potentially issued from a free space propagation (i.e. the probability that a following received path is a direct path is null), so that the search for new upcoming candidates is performed in a smaller set of predicted waveforms.

D. Estimation Quality Indicator

An Estimation Quality Indicator (EQI) can be always associated with each surviving candidate at each iteration of the modified CLEAN using rejection windows. The quality indicator $m^{(n)}(j)$, calculated at the $n$-th layer for the $j$-th candidate, can be defined as follows:

$$m^{(n)}(j) = \mathcal{P}_{\text{max}}(j) \sum_{n=1}^{\bar{n}} \sqrt{\bar{\sigma}_{j,n}}$$

(8)

where $\mathcal{P}_{\text{max}}(j)$ is the maximal probability corresponding to the CIS carried by the $j$-th candidate, $\bar{\sigma}_{j,n}$ is the estimated energy of the $n$-th detected path for the $j$-th tree node. Note that $\sqrt{\bar{\sigma}_{j,n}}$ corresponds to the maximal cross-correlation value taken over time shifts, provided by the discussed CLEAN algorithm for the $j$-th candidate and the $n$-th path.

VII. SIMULATIONS

A. Parameters

Results obtained with the discussed algorithm are provided in a simplified indoor scenario, such as a rectangular room ($D_x = 6$ m $D_y = 5$ m) with brick walls. The transmitter and receiver coordinates have been arbitrary chosen, namely...
(x1,y1) = (1.1,1.15) m and (x7,y7) = (3.4, 4.6) m. The Power Spectral Density (PSD) of the transmitted signal complies with the FCC UWB mask (e.g. [1]) and the simulated system employs a Pulse Repetition Period (PRP) of 250 ns. The signal takes up a bandwidth of 2 GHz at −10 dB of the PSD maximum, centred around 4.5 GHz. The received signal is affected by thermal noise (i.e. Gaussian, $N_0 = −174$ dBm/Hz) filtered in the signal band. Concerning the simulated front-end, a noise figure of 3 dB accounting for a more realistic receiver and a UWB Conical Monocone Antenna (CMA) (e.g. [9]) are considered. A draw of the received signal, obtained by the Ray-Tracing simulation tool described in [10], is shown on Figure 4. The resulting times of arrival are reported in Table I. Finally, the selection threshold discussed in Section VI-C is set to $\gamma = 0.85$.

![Image](image_url)

Fig. 4. Received signal corresponding to the simulated geometrical scenario

### B. Complexity Comparison

As it has been explained in Section VI-C, the Blind Algorithm shows an exponential complexity growth with the number of detected paths. The average complexity saved using the algorithm described in this paper is evaluated as the average number of layer candidates that have not been selected. Actually, considering a new candidate corresponds to performing the two main tasks: cross-correlation calculation and signal cleaning. Numerical results showing the simulated average complexity saving are reported in Table II.

Complexity saving is due to the selection threshold $\gamma$ and to the statistical approach (i.e. the elimination of configurations having null probability). As the algorithm applies the selection threshold at layer $n$, it limits the number of children for a given node (i.e. the number of candidates to be analysed at layer $n + 1$). Once the selection process has finished, the null probability criterion enables to discard configurations corresponding to geometrical aberrations, decreasing further the number of selected candidates to be processed in layer $n + 1$. In Table III the average percentages of null probability levels survive up to this layer. In addition, it is interesting to note that very good estimates for the simulated configuration are always present for each path, even if rare.

According to the assumed scenario, when a configuration of five single-bounce reflected paths is obtained at the last layer (i.e. the direct path has not been associated with a free space propagation), the material estimation for one path is for sure wrong. In order to find which path among the five single-bounce detected paths is not a single-bounce path, EQI as described in Section VI-D is used. Therefore, the configuration of the four paths leading to the maximum EQI value will survive, while the eliminated path will be labelled as “unknown”. As path 1 is not a single-bounce one, the optimal EQI would always label path 1 as “unknown”, if the remaining

### C. Last Layer Analysis

As a preliminary approach, the surviving candidates at the last layer are analysed. For each path, an empirical probability density of joint angular errors (i.e. errors on AoA-AoD and IAIS) has been calculated over the last layer candidates. Results dealing with the direct path and two simple-bounce reflected paths are presented on Figure 5 up to 7. The AoD-AoA joint error is obtained as the Euclidean distance between the tested and the estimated directions on the AoD-AoA plane (e.g. [9]). Consequently, AoD-AoA errors have the dimension of an angle. The IAIS cluster error is simply obtained as the absolute value of the difference between the true IAIS index and the estimated one.

First of all, as it was expected, well-isolated paths are more easily estimated than overlapping paths. As an evidence, final candidates carry a very little number of low-error estimates for path 1 (see Figure 5), while the peak of the joint error distribution shows not very high both AoD-AoA and IAIS errors (i.e. compared to maximal error values). On the contrary, the joint error distribution for path 2 estimates is rather concentrated in an area where IAIS error is severe (see Figure 6). Finally, the well-isolated path 5 is affected by a low joint error (see Figure 7). Anyway, reported distributions deal with all the surviving candidates on the last layer (i.e. without applying any criterion eliminating less probable estimates). So, it seems reasonable that estimates with very different quality levels survive up to this layer. In addition, it is interesting to note that very good estimates for the simulated configuration are always present for each path, even if rare.

![Image](image_url)

### Table I: Times of Arrival in [ns]

<table>
<thead>
<tr>
<th>Path 1</th>
<th>Path 2</th>
<th>Path 3</th>
<th>Path 4</th>
<th>Path 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>16.3</td>
<td>18.6</td>
<td>20.8</td>
<td>27.8</td>
</tr>
</tbody>
</table>

### Table II: Average complexity saving using the discussed algorithm in comparison with BA

<table>
<thead>
<tr>
<th>Layer 2</th>
<th>Layer 3</th>
<th>Layer 4</th>
<th>Layer 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>18%</td>
<td>51%</td>
<td>81%</td>
<td>93%</td>
</tr>
</tbody>
</table>

### Table III: Average percentage of saved complexity per node using selection threshold $\gamma$

<table>
<thead>
<tr>
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<th>Layer 2</th>
<th>Layer 3</th>
<th>Layer 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>18%</td>
<td>18%</td>
<td>29%</td>
<td>20%</td>
</tr>
</tbody>
</table>

### Table IV: Average percentage of null potential probability candidates

<table>
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<th>Layer 3</th>
<th>Layer 4</th>
<th>Layer 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>27%</td>
<td>45%</td>
<td>54%</td>
<td>25%</td>
</tr>
</tbody>
</table>
paths were correctly detected (i.e. without errors in estimating the time location of multipath components). As the algorithm sometimes gets wrong in estimating the time position of a multipath component (e.g. due to inefficient signal cleaning), a limited number of “unknown” candidates should correspond also to the four single-bounce paths.

Table V reports the rate of “unknown” detection for each path: only a small number of “unknown” estimates is associated with path 1. This result is rather different from expectation, highlighting the weakness of the EQI in detecting “unknown” paths. However, note that the channel state knowledge (i.e. LOS or NLOS) is not required by the algorithm, what represents a general but pessimistic case. For instance, if a LOS state was assumed (e.g. through LOS/NLOS identification algorithms) the ambiguity about “unknown” paths would be easily solved out. Nevertheless, the estimation problem still has to be better constrained introducing a statistical description for other variables in addition to IAIS. As a matter of fact, EQI would perform better if its probability factor was more discriminating.

VIII. CONCLUSION

This paper has presented a tree approach method for AoA, AoD and IAIS estimation in the context of IR-UWB communications. The complexity of the discussed algorithm is lower than that of the Blind Algorithm, because of the selection threshold based on cross-correlation values and the criterion eliminating all the configurations leading to a null probability (i.e. with respect to IAIS). As the employed Estimation Quality Indicator seems sometimes not to properly handle a set of five single-bounce estimates, the discriminating capability of EQI will be improved in future works. As an example, EQI enhancements could rely on the probability of AoA (or AoD) spreads and received time differences. Such improvements are also expected to provide further complexity reduction.

IX. ACKNOWLEDGEMENT

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REFERENCES