UWB Channel Modeling: a Markovian Formulation based on Degradation Level Concept

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Abstract—Ultra wide band (UWB) thanks to its physical characteristics became one of most suitable technology for indoor and outdoor personal communications. Many works have already treated problematic involving UWB transmission channel. However, at the best of our knowledge, all proposed model work at the physical level or they investigate only some aspects of channel interactions. Instead, in our work, we provide an approach to obtain an accurate high level channel model based on Discrete Time Markov Chain (DTMC) modeling useful in every simulative context. In particular, our model is based on the concept of error trace analysis and on degradation level of a given observation window: we do not analyze the single packet, but we fix an observation window and we evaluate the degradation level of the link computing the Packet Error Rate (PER) relative to the specific window. This new approach is more accurate than classic Gilbert-Elliot (G-E) model, 3rd order Markov model and Markov based Trace Analysis (MTA) Model as a comparative analysis, based on the occurrence of correctly and wrongly received packets, showed.

Index Terms— UWB channel, DTMC, Error Trace Analysis, Degradation Level Concept.

I. INTRODUCTION

UWB systems take their name from very large bandwidth employing in transmission (Federal Communication Commission, FCC, defines UWB any system whose transmission bandwidth greater than 500 MHz) achieved through baseband impulse of very short duration (few nanosecond) [1]. These last characteristics make these systems unique: the UWB can employ unlicensed frequency (FCC directives), they are able to transmit at low power (UWB signal power is comparable with background noise) without affecting the receive operations, simple hardware architectures allowing low cost device, no significant multipath fading due to fine time resolution and possibility of high data rates. In this work, we focalized our attention on high rate UWB networks and in particular, we considered Direct-Sequence spreading based UWB (DS-UWB) systems. DS-UWB realizes a Wireless Personal Area Network (WPAN) with data payload communication capabilities up to 1320 Mbps [2]. Moreover, such ultra-wide bandwidth gives rise to important differences between UWB and narrowband channels, especially with respect to the number of resolvable paths and arrival times of multipath components. Many works have already treated the channel modeling of UWB networks, taking into account multipath fading, shadowing and path loss phenomena ([3],[4],[5]). In particular, the model proposed in [5] has been considered as the model better fitting the UWB channel characteristic: in fact it has been assumed as reference by IEEE. However, in [5] the authors model the phenomena of wireless channel through an impulse response, therefore, this model and most of UWB channel models are not indicated to work at the packet level and this is not an easy problem, especially if, for example, we want to investigate also the higher levels of ISO/OSI architecture. For this purpose, contrarily to ([3],[4],[5]), we approach the channel modeling problem through a Markovian analysis ([6],[7]) providing a procedure to obtain high level models. In our work, starting from model description in [5], we describe a procedure to obtain a specific model for a given data rate, scenario (that is Line of Sight, LOS, or No-Line of Sight, NLOS) and average noise power level starting from simulation results collected through a DS-UWB Matlab simulator. As in [8], we applied the packet error trace analysis, but contrary to [8], in our work we introduce the concept of degradation level: we do not analyze the single packet, but we fix a time window and we evaluate the degradation level of the link computing the Packet Error Rate (PER) relative to the specific time window. This approach increases the number of states respect to the simply G-E model [7], but we proof that it improves the accuracy of the model; in particular, we will show that it is convenient to add new states to the DTMC until the last added state satisfies transient propriety for all remaining states.

In the following, we will describe the related work in section II and the reference scenario in section III. Then, in section IV, we will give some notions about DTMC and trace analysis and we will describe our model with some examples. Finally, in section V, we will analyze the performance evaluation comparing our model with the G-E, 3rd order Markov and MTA models and, in the last section, the conclusions will be summarized.

II. RELATED WORKS

A recent and important field of research is the study of physical phenomena involving UWB transmission: in fact such ultra-wide bandwidth gives rise to important differences between UWB and narrowband channels, especially with respect to the number of resolvable paths and arrival times of multipath components. Many works have already treated the channel modeling of UWB networks, taking into account multipath fading, shadowing and path loss phenomena ([3],[4],[5]). In particular, the formal model adopted to test UWB physical layer standards proposals and it is a valid model for all UWB communications in the 3-10 GHz frequency range, so we choose this model as reference in order to carry out our analysis. However, although this is a good model, it can work only at the bit level because it models the phenomena of wireless channel through an impulse response. Therefore, this model and most of UWB channel models are not suitable to work at the packet level and this is not an easy problem, especially if, for example, we want to investigate also the higher levels of ISO/OSI architecture. For this purpose, contrarily to ([3],[4],[5]), we approach the channel modeling problem through a Markovian analysis providing a procedure to obtain high level models. Many works have already treated the channel modeling using a statistical approach based on Markov Chain. In [8], the authors proved that trace exhibits stationary proprieties for small temporal windows and so they propose to subdivide the trace in error free period and lossy period, where this last process is again modeled as a 6th order Markov Chain. Their algorithm, based on the error frame analysis is called MTA. MTA is extremely suitable to capture statistics such as the distribution of wrong packets in the trace, but it is unable to capture 2nd order statistics as PER or autocorrelation function of frame error level. This problem is solved in [9]: the authors propose a new model, a simple ON-OFF model, based on two-states semi-Markov approach in which a particular geometric distribution is employed to capture both first and second order statistics. This approach offers better performance than MTA. However, on the other hand, it introduces a consistent increase of complexity. In [10] the authors revisited and enhanced the model proposed in [9]: they confirmed the two-states semi Markov approach but they suggested to employ a logarithmic distribution for the holding time of each state instead.
of the geometric distribution. Another important approach is the GAP model proposed in [11], in which the authors proved that, under specific conditions, the packet errors can be modeled only as a Markov chain without constant transition probabilities. Instead in [12] was proposed the Bipartite model offering a better approximation of error distribution respect the above mentioned approaches to the detriment of a greater complexity due to a lot of parameters to estimate in order to set the model. In [13], the authors showed that can be sufficient a simple two-states Markov Chain in order to model the packet loss in 802.11b link, contrarily to GSM system for which more complex models are needed due to error characteristics. However, in [13] is also shown that bit error modeling requires more accuracy and so they proposed a Hierarchical Markov Model (hMM) for these statistics. These last considerations lead us to consider as reference for our analysis the G-E model (that is a simple two-states model) described in [7] and the error analysis presented in [8]. In particular, in accordance to [8], we observe that channel characterization can be captured by a packet error trace, but contrary to [8] in our analysis we introduce the concept of degradation level: we do not analyze the single packet, but we fix a time window and we evaluate the degradation level of that set of packets. Furthermore, in [7] the authors considered only two states, the Bad state and the Good state, in order to describe channel dynamics. In [8], as previously mentioned, the authors propose the MTA algorithm: they extend the Bad state in more states if the stationary property is not satisfied subdividing the original trace in two segments. They start by assumption that a time-variant wireless channel, such as GSM channel, does not present a stationary trace and so a decomposition of the original trace is needed to better describe channel behavior.

III. REFERENCE SCENARIO

In this work, we focalize our attention on DS-UWB physical layer standard. In order to collect simulation data to carry out trace analysis a physical simulator based on Matlab has been realized. DS-UWB provide a WPAN with data payload communication capabilities up to 1320 Mbps [2]. In order to take into account the effect of UWB multipath channel we use the IEEE model described in [5]. As the channel measurements showed multipaths arriving in clusters, this model for the time-of-arrival statistics uses the Saleh-Valenzuela approach [4]. The model proposed in [5] provides four different multipath fading scenario: CM1 (that describes a LOS, scenario), CM2 and CM3 (that describe two different NLOS, scenarios) and CM4 (that depicts a very extreme NLOS scenario). Further details can be found in [5]. Moreover, Additive White Gaussian Noise (AWGN) effects, modelled as the noise of parametric power level, are added to the channel realizations. At receiving side, we have instead used a Minimum Mean Square Error (MMSE) receiver ([14],[15],[16],[17]). These receivers are capable of combining energy from the dense multipath return of UWB and it is more performing than a four or eight fingered RAKE receiver ([14],[15]). In particular we have employed a linear equalization MMSE receiver even if in [16] the authors have shown that decision-feedback equalization MMSE offers better performance specially for high date rate, but equalization is also more complex in this case. Besides, in [16] and [17] the MMSE equalization are combined with the RAKE receiver in order to further improve the performance, however in [9] and [11] are shown that the MMSE receiver alone can be sufficient to recover the data reducing in this way the complexity. For this purpose, in this work, we adopt a simply linear equalization MMSE receiver to recover the transmitted information. In particular, this receiver uses an adaptive algorithm called Normalised Least Minimum Square (NLMS) to upgrade weights vector w. Furthermore, in our simulations, we use a MMSE receiver with 16 taps per observation window and a step size of 0.5.

Besides, we work in the piconet channel 1 of the lower band with a chip rate of 1313 MHz and, for every simulation campaign, we fixed the transmission power to -9 dBm (according with FCC mask) and the packet size to 128 bytes.

IV. DISCRETE TIME MARKOV CHAIN

A. Markov Chain Definition

A DTMC is defined as a discrete-time stochastic process assuming discrete values such as process evolution starting from observation time depending only on the current state ([6],[7]). This concept can be expressed by the following formula:

\[ p_{ij} = P(X_n = j | X_{n-1} = i) \]  (1)

where \( p_{ij} \) is the probability that the process is in the state \( j \) at the time \( t_n \) if at the time \( t_{n-1} \) it is in the state \( i \). These probabilities can be rewritten in a matrix form as follows:

\[ P = \begin{bmatrix} p_{00} & p_{01} & \cdots & p_{0n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n0} & p_{n1} & \cdots & p_{nn} \end{bmatrix} \]  (2)

\( P \) is called transitions probability matrix and it can be proved that it is a stochastic matrix [6], so the sum of the elements of each row is always 1:

\[ \sum_{j=0}^{n} p_{ij} = 1 \quad i = 0,1,\ldots,n \]  (3)

In particular, \( p_{ij} \) measures the constant trend to leave the state \( i \), in fact, from Markov chain theory, we know that the mean \( i \) state sojourn time is exponentially distributed with a law of parameter \( p_{ij} \) ([6],[7]). Before proceeding with our analysis some definitions must be given:

1. Transition probabilities are time-invariant (stationary propriety);
2. State \( j \) is reachable from state \( i \) (denoted with \( i \rightarrow j \)) if \( p_{ij} \neq 0 \);
3. A state \( i \) is transient if from state \( i \) we can reach some state \( j \), from which it is impossible to get back to state \( i \), that is: \( \exists j \in S \text{ such that } i \rightarrow j \text{ and } j \not\rightarrow i \); where \( S \) is the state set;
4. In order to investigate the complexity of Markov Chain, we must give the definition of Conditional Entropy. The Conditional Entropy is a measure of the amount of information of a element of the trace knowing the previous history. The amount of past history necessary to predict the next element of the trace depends on Entropy Order: an \( i \)-th entropy order of 0 indicates that knowing the last \( i \) elements of the chain totally predicts the next element on the chain. Therefore, an higher order of conditional entropy means a more accurate prediction of the next element. On the other hand, a decreasing of conditional entropy (and so an augment of entropy order) corresponds to an increasing of complexity of DTMC measured in number of states: in fact for the traditional markovian approach an entropy of order \( i \) gives a complexity of \( 2^i \) states. It means that an exponential law relates the entropy order and the number of states in the traditional approaches such as ([7],[8]). Instead, in our approach the entropy order and the number of states (and so the complexity of Markov Chain) are related by a linear law because we consider two sequences of length \( i \) different if they have a different number of 1 (wrong packets): the different position of a wrong packet in the two sequences do not make them distinct. Therefore, on the basis of what previously mentioned, in our model an entropy of \( i \) order gives a complexity of \( (i+1) \) states. In particular in Fig. 1a, we show as in our model the number of states is a linear function of entropy order contrarily to traditional model in which an exponential law ties entropy order and number of states. According with [8], the conditional entropy is given by:

\[ H(i) = \sum_{j=0}^{n} p(j) \sum_{\gamma \in \Omega(j)} p(\gamma | j) \log \left( \frac{p(\gamma | j)}{p(j)} \right) \]  (4)
where $\tilde{x}$ is one of $2^i$ possible sequences of length $i$ or, following our approach, $\tilde{x}$ is one of $(i+1)$ sequences of length $i$, $p(\tilde{x})$ is the probability of having the specific sequence $\tilde{x}$ in the trace, $p(\tilde{y}|x)$ is the conditional probability of having the sequence $\tilde{y}$ followed by $y$.

5. We use the standard error [6] as a measure of error between two vectors of samples $x$ and $y$, and we define it as:

$$\epsilon_x = \sqrt{\frac{1}{n_1+n_2-2} \left( \frac{1}{n_1} \sum_{i=1}^{n_1} x_i^2 - \frac{1}{n_2} \sum_{i=1}^{n_2} y_i^2 \right)}$$

(5)

where $n_1$ and $n_2$ are respectively the dimension of vectors $x$ and $y$, whereas $X$ and $Y$ are given by:

$$x = \sum_{i=1}^{n_1} x_i / n_1, \quad y = \sum_{i=1}^{n_2} y_i / n_2$$

(6)

6. The mean state sojourn times must follow an exponential law.

7. We verify the stationarity propriety of the trace through the Reverse Arrangements Test [18].

Therefore, we can affirm that a generic stochastic process is a DTMC if it satisfies the stationary propriety (that is transaction probabilities are time-invariant), the state sojourn mean times are exponentially distributed and the number of states is finite ([6],[7]).

**B. Error Trace Analysis**

In accordance to [8], we observe that UWB channel characterization can be captured by a packet error trace. In our work, a packet is simply a sequence of bits. Furthermore, a packet is correctly received if no wrong bits are detected and consequently a packet is not correct if almost a bit is erroneously received in the sequence. In [8], the authors considered only two states, the Bad state and the Good state, even if they extend the Bad state in more states if the stationary property is not satisfied. Contrarily to [8], in our analysis we introduce the concept of degradation level: we do not analyze the single packet, but we fix a time window (consisting in a given number of packets) and we evaluate the degradation level of the link computing the PER relative to the specific window. Repeating recursively this operation for all traces, we can create a new trace (called 'windowed trace') in which each state represents a specific level of degradation. We underline as the size of time window, denoted with $w$, affects the transition probabilities and so Markov Chain evolution (we remember that if $w$ is set to 1 then DL-DTMC model degenerates in G-E model). Another important step is to determine the degradation level number, that is the states number, and so the degradation thresholds PER associated to the states: on the basis of these thresholds, we can establish the association of the current observed time window to a specific state. In this work, our approach is to set the states number $|S|$ to $w+1$: in this way, we can have discrete values of relative PER. This simple approach is very efficient because it allows to tie the degradation level (and so the state representing a specific degradation of the wireless channel) directly to the number of wrong packets in the considered observation window. This concept can be expressed by the following expression:

$$\frac{i \text{ wrong packets}}{w} \rightarrow \text{PER}_{\text{rel}} = \frac{i}{w} \to \text{we are in the } i\text{-th state}$$

(7)

For example, the “0” state (that is the no degradation state) is characterized by a null relative PER meaning that in the observed window no packets are wrongly received. Instead the “$w$” state is characterized by relative PER of 100% because in the observed window all packets are wrongly received. The scheme of a generic $(w+1)$ states DTMC model based on the concept of degradation level is shown in Fig. 1b.

**C. Degradation Level based DTMC Channel Modeling**

In this subsection, we provide the procedure to model a DL-DTMC. Before proceeding with the algorithm, the stationary propriety of the process must be evaluated. We verified stationarity propriety using the Reverse Arrangements Test described in [18]. If the trace passes the stationary test, we can proceed with the following steps:

- Set $w=0$;
- Set $P=[1]$; ( [ ] denotes the null matrix)
- Repeat
- $w=w+1$;
- $P_{\text{prev}}=P$; (it is intended as a matrix assignment)
- $|S|=w+1$;
- Create a windowed trace with the size of time window set to $w$ applying (7);
- Compute the $p_{ij}$ probability of $P$ applying the following formulas:

$$p_{ij} = \frac{T_{ij}}{N_{i}}, \quad j = 0, 1, \ldots, w \quad i \neq j$$

(8)

where $T_{ij}$ is the number of transition from $i$ state to a generic $j$ state, while $N_{i}$ is the number of $i$ state;
- From the stochastic property of matrix $P$, we compute

$$p_{ij} = 1 - \sum_{j=0, j \neq i}^{w} p_{ij}$$

(9)

- Verify the distribution of the state sojourn time using the Kolmogorov-Smirnov (K-S) test and set $B=\text{false}$ if at least a test fails;
- Until for the last added state $i$ the transient propriety is verified for each considered states $j\in S$ or $B=\text{false}$;
- Set $P=P_{\text{prev}}$; (it is intended as a matrix assignment).

The modeling procedure is now completed because the Markov chain can be completely determined by matrix $P$ and by distributions of state sojourn time.

**D. Examples of DL-DTMC modeling**

Due to lack of space, in the following, in order to better explain the procedure to create a DTMC model based on degradation level, we can show only two examples for different data rates covering
also different levels of noise and scenarios described in [5].

In this first example, we set the data rate to 28 Mbps and we consider the CM4 scenario with an average power level of -30 dB. Our goal is to show as the DTMC characteristics vary increasing the length of observation window (and so the states number). In particular, we observe that is convenient to add further states to the chain until the efficiency improving is consistent: generally this condition is reached when the new added state is a transient state (see subsection IV.A). The first step is to evaluate the stationarity propriety of the original trace using Reverse Arrangements Test [18]. In Fig. 2a, we plot the mean square value for each time interval in which our trace has been divided: we can see that these values do not present any underlying trend as also confirmed by total reverse arrangement value falling in the interval expected (see [18] for further details). Instead, in Fig. 2b, we show the conditional entropy as a function of entropy order for the traditional approach and for our approach: we can see as for the chosen entropy order, that is 4 for this configuration (see in the following), our model gives a entropy value of 0.0139 contrarily to the traditional model giving a value of 0.0137. Therefore our model presents a worsening of entropy of 1.44% compared to the traditional approach, but on the other hand the our approach reduces the complexity of the model: in fact if the entropy order is set to 4, our approach requires 5 states while the traditional approach requires 16 states, so in this case we have a complexity reduction of 68.75%. Hence, after having verified the random propriety, we can proceed to create the windowed trace and to compute states transition probabilities for different length. We omit the degenerate case (that is \( w = 1 \)) because it is equivalent to the G-E model (two states model), so we start our analysis from three states model (in which the length of the window is set to 2). We denote with \( w \) this case and in particular we obtain:

\[
P_e = \begin{bmatrix}
0.670 & 0.3694 & 0.0002
\end{bmatrix}
\]

while for the four states model, with \( w = 3 \), (called \( w_3 \)) we have:

\[
P_e = \begin{bmatrix}
0.618 & 0.0464 & 0.0003 & 0
\end{bmatrix}
\]

Finally we fix \( w \) to 4 and we modeled the five states DTMC (denoted with \( w_4 \)) obtaining the following matrix:

\[
P_e = \begin{bmatrix}
0.8023 & 0.1068 & 0.01 & 0.0009 & 0
0.8571 & 0.1319 & 0.0073 & 0.0037 & 0
0.167 & 0.0033 & 0 & 0 & 0
0 & 0 & 0 & 0 & 0
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

We can see as in the \( w_4 \) model the state “4” is transient because it is impossible to reach it from the other states: in fact all probabilities \( p_{i,j} \) are null. This means that the new further added state to the chain do not improve the efficiency of the model, so in this case the best model is the four states DTMC. This trend is graphically confirmed by Fig. 3a, where the occurrences of correctly received packet in the original trace and in the artificial traces (for further details on the generation of artificial trace see the next section) are compared: we can see as the efficiency of the models rises with the increase of the states number until the new state added is transient. In this last case the efficiency of the model degrades respect the \( w_3 \) model, so we can affirm that for this configuration the best fitting model is the four states DTMC. This trend is also confirmed by standard error committed by 4 states model respect to the correct packet distribution of empirical data (0.6468) that is less than standard errors committed by 3 and 5 states models respectively of 0.4986 and 0.8978. Chosen the \( w_4 \) model, the next step is to analyze the states sojourn time. Applying the K-S test, we verify that all states sojourn time are effectively exponentially distributed. In particular, for the “0” state in the case of \( w_4 \) model we obtain that the exponential distribution better fitting experimental data distribution, that is the distribution minimizing standard error [12], is an exponential with \( \mu = 11.1821 \) introducing a standard error of 0.2149. In Fig. 3b, we show the “0” states sojourn time distributions and its approximation exponential distributions for \( w_4 \). The second example regards CM2 scenario with a 500 Mbps data rate and a mean noise power of -50 dB. After verifying stationarity propriety, we obtain that the best model is a six states DL-DTMC model characterized by:

\[
P_e = \begin{bmatrix}
0 & 0 & 0 & 0 & 1 & 0
0 & 0.05 & 0.15 & 0.3 & 0.5
0 & 0.027 & 0.0721 & 0.1802 & 0.2613 & 0.4095
0.0033 & 0.0065 & 0.0409 & 0.1694 & 0.3648 & 0.4072
0 & 0.01 & 0.0601 & 0.1402 & 0.3084 & 0.4063
0 & 0.0093 & 0.0552 & 0.1555 & 0.3281 & 0.4548
\end{bmatrix}
\]

Furthermore, all states sojourn times are exponentially distributed as K-S test confirms.

V. PERFORMANCE EVALUATION

The DS-UWB simulator (employed to collect data) and our algorithm are implemented through Matlab tool. In this section we describe the procedure to generate an artificial trace using DTMC statistics obtained by our model. Furthermore we will compare the artificial trace obtained by our model with artificial trace generated by G-E model and 3rd order Markov model in order to prove as DL-DTMC model best fits the experimental trace. The particular characteristics of time-invariant UWB multipath channel combined with an AWGN channel make the errors independent on time: it means that the wrong packet in the traces are always randomly distributed and so the stationarity propriety is always verified for the considered UWB architecture.

A. Artificial Trace Generation Algorithm

The algorithm for trace generation from DTMC model based on the concept of degradation level is composed by the following steps:

- Set \( N \), the number of packets to generate;
- Assume that the starting state is not the degradation state;
- Repeat the next steps until \( N \) packets are generated:
  - If current state is “\( i \)” then choose the \( (i+1) \)-th row of transition matrix \( P \);
  - On the basis of these probabilities you choose the next state;
  - Add a window of \( w \) packets to the trace. The number of wrong packets depends on the degradation level associated to the current state. Distribute the wrong packets in the window in a random way;
  - Leave current state moving to new chosen state.

Note the assumption of choosing always “0” as initial state is not restrictive for the our model: in fact independently on this the model dynamically evolves following its transition probabilities. Methods to generate the artificial traces with G-E, 3\( ^{rd} \) order Markov and MTA model can be found respectively in [7] and [8].

B. Trace Comparison

Starting by first configuration, we generate an artificial trace following the previous steps. In particular, we have generated the artificial trace using the best fitting DL-DTMC model, the G-E model, the MTA model and 3\( ^{rd} \) order Markov model proving that our model better approximates the experimental trace trend. In Fig. 3c, we compare the occurrences of wrong received packets in this trace with that of one of the trace obtained via simulation from G.E, 3\( ^{rd} \) order Markov, MTA and our model. We can see as the distribution of the wrong packets in the artificial trace obtained by our model is similar to the distribution of experimental trace as the error statistics, summarized in Table I, confirm. This is also confirmed by the standard error committed by our model (0.0152) that is less than standard error committed by G-E model (0.0159) MTA model.
(0.0405) and 3rd order Markov model (0.0218). The second configuration concerning the 500 mbps data rate in a CM2 scenario with an average noise power threshold of ~50 dB. For this configuration the best fitting DL-DTMC model is the six states model characterized by (13). Analyzing the occurrences of wrong received packet (see Fig. 3d), we can observe as our model closer perfectly to distribution of correctly received packet extrapolated by trace obtained via simulation contrarily to 3rd order Markov model, MTA model and G-E model that show a worse fitting. For the distribution of the errors in the trace, we note that the model better approximating channel behaviour is the DL-DTMC model as statistics, summarized in Table II, confirm. In particular, our model introduces a standard error of 0.0291 contrarily to G-E, MTA and 3rd order Markov models introducing respectively an error of 0.0298, 0.1916 and 0.041.

Table I. Error Trace Statistics for first configuration.

<table>
<thead>
<tr>
<th>Trace type</th>
<th>µ</th>
<th>St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>experimental</td>
<td>1.0977</td>
<td>0.3126</td>
</tr>
<tr>
<td>G-E model</td>
<td>1.0971</td>
<td>0.3523</td>
</tr>
<tr>
<td>3rd order Markov</td>
<td>1.4143</td>
<td>0.6385</td>
</tr>
<tr>
<td>MTA model</td>
<td>1.0726</td>
<td>1.1504</td>
</tr>
<tr>
<td>4 States DL-DTMC</td>
<td>1.0945</td>
<td>0.5334</td>
</tr>
</tbody>
</table>

Table II. Error Trace Statistics for second configuration.

<table>
<thead>
<tr>
<th>Trace type</th>
<th>µ</th>
<th>St. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>experimental</td>
<td>6.54272</td>
<td>5.9723</td>
</tr>
<tr>
<td>G-E model</td>
<td>6.68204</td>
<td>5.7333</td>
</tr>
<tr>
<td>3rd order Markov</td>
<td>8.38776</td>
<td>11.681</td>
</tr>
<tr>
<td>MTA model</td>
<td>5.79619</td>
<td>33.596</td>
</tr>
<tr>
<td>6 States DL-DTMC</td>
<td>6.52574</td>
<td>6.4929</td>
</tr>
</tbody>
</table>

VI. CONCLUSIONS

In this work, we considered a UWB WPAN based on DS-UWB physical layer and we have considered a multipath channel, further worsen by AWGN, based on channel model presented in [5]. However, this last channel model and many other channels models present in literature work at the bit level and so they are not suitable in those contexts in which an high level approach is needed. In our work instead, we provide a high level UWB channel model based on the concept of degradation level DTMC modelling useful in every simulation requiring to work at the packet level. For this purpose, we use the packet error trace analysis to model multi-states channel model. The obtained models are therefore tested generating artificial traces and comparing them with trace obtained by experimental simulation and with the artificial trace obtained by classic G-E Markov chain model, MTA model and 3rd order Markov model. Performance evaluation and have been proved that our model better fits experimental trace respects to the MTA model, G-E model and 3rd order Markov model. Furthermore, the goodness of our approach is also confirmed by error trace statistics and in particular by a lower error standard committed respect to the traditional approaches and MTA approach. Finally, we note that the number of additional states, needed to obtain a better accuracy, depends on the specific operative conditions and so on scenario, data rate and noise power level.

REFERENCE