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A Novel Wideband Dynamic Directional Indoor Channel Model Based on a Markov Process

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Abstract-A novel stochastic wideband dynamic spatiotemporal indoor channel model which incorporates both the spatial and temporal domain properties as well as the dynamic evolution of paths when the mobile moves is proposed based on the concept of a Markov process. The derived model is based on dynamic measurement data collected at a carrier frequency of 5.2 GHz in typical indoor environments. Multipath components are estimated using the super-resolution frequency domain spacealternating generalized expectation maximization algorithm prior to identification of path "birth" and "death" using a new data analysis method. Analysis shows that multiple births and deaths are possible at any instant of time. Furthermore, correlation exists between the number of births and deaths. Thus, an M-step 4-state Markov channel model (MCM) is proposed in order to account for these two effects. The spatio-temporal variations of paths within their lifespans are taken into consideration by the spatio-temporal vector which was found to be well modeled by a Gaussian probability density function while the power variation can be modeled by a simple low-pass filter. In addition, the methodology used to extract the MCM parameters from the measurement data is also presented. Due to the distinction in the birth-death statistics, the model is generalized through segmentation of the measurement runs and can be completely parameterized by several sets of Markov parameters associated with the type of environment and scenario under consideration. The implementation of the model is also detailed and, finally, the model is evaluated by comparing key statistics of the simulation results with the measurement results.

Index Terms—Indoor radio communication, Markov processes, multipath channel, radio propagation.

I. INTRODUCTION

C HANNEL modeling is an important research topic in wireless communications. A realistic radio channel model that provides detailed knowledge of the radiowave propagation mechanisms is essential for the successful deployment of future

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wireless systems. The propagation channel parameters are time varying due to the motion of the mobile terminal (MT) and changes in the surrounding objects, which can then be modeled by a stochastic process. The motion of the MT introduces both small- and large-scale variations in the received signal. The work reported here focuses on the large-scale variation induced by the motion of the MT such as fluctuations of the number of active paths, transitions where paths appear and disappear, variations in the propagation delays and powers, and the changes of the direction of arrivals as the MT moves along its trajectory.

In recent years, many extensive studies have been carried out in order to gain a more profound knowledge of propagation channels. Numerous channel models have been reported in the literature [1], [2]. A major shortcoming of the currently available models is that they do not consider the dynamic behavior of the channels, i.e., the appearance and disappearance of paths due to movement of the MT. This is mainly due to the lack of dynamic measurement campaigns to support realistic modeling of a dynamic channel. To the best of the authors' knowledge, only two models have appeared in published literature which model the dynamic properties of the indoor propagation channel. The first model is a stochastic spatial channel model for indoor propagation environments proposed by Zwick et al. [3], [4]. This model is based on the idea of physical wave propagation. A deterministic raytracing tool is used to produce the huge data sets required for statistical evaluation of the parameters of the proposed model and measurements are used for verification purposes. A key assumption made in this model is that the appearance and disappearance of paths to be statistically independent and, thus, can be modeled by a simple birth-death (B-D) process. Later, a Markov process is used to model the line-of-sight (LOS) path separately from all other paths. Note that the above model differs from the model proposed in this paper in terms of the modeling concepts, approaches, and assumptions as will be discussed in detail in the rest of the paper. The second model is a temporal domain model proposed by Nielsen et al. [5]. However, the lack of dynamic spatial information in Nielsen's model does not allow any realistic evaluation of smart antenna systems that would exploit both temporal and spatial domains of the channel. As smart antennas have emerged as one of the most promising candidates to maximize wireless capacity throughput [6], the underlying models must characterize the spatio-temporal properties as well as the dynamic evolution of paths as the MT moves around the environment.

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Modeling the appearance and disappearance of paths is essential for the next generation of wireless systems (e.g., HIPERLAN/2 and IEEE 802.11a for indoor environments), which are expected to support mobile users at very high data rates and to provide a more realistic simulation scenario for performance evaluation. This is essential as the statistical characteristics of the channel may change significantly with the displacement of the MT from one location to another. Furthermore, modeling the dynamic behavior of the channel is vital for performance evaluation of any channel tracking algorithms such as beam-forming. Hence, a static channel *model* with constant parameter settings within a local region is insufficient to realistically model a time-variant environment that is subject to movement of both the MT and surrounding scatterers. Therefore, a dynamic channel model that is capable of tracking the dynamic evolution of paths as the MT moves along its trajectory is necessary.

The objectives of this paper are threefold. Firstly, to study in more detail the dynamic behavior of indoor propagation channels in order to improve the understanding of the time-varying propagation mechanisms and to provide information for dynamic spatio-temporal channel modeling purposes. Secondly, to propose a new stochastic channel model based on the Markov process that will take into account the time-varying properties of the channel by incorporating the dynamic evolution of paths when the MT is in motion. The power and spatio-temporal variations of paths within their lifespans which were found to be well modeled by a Gaussian probability density function (pdf) and a simple low-pass filter (LPF), respectively, are also investigated. Thirdly, the proposed model is evaluated by comparing the statistical behavior of the measurement results with the simulation results.

The paper is organized as follows: Section II describes the measurement setup and environments. Section III presents the data analysis and processing techniques to extract multipath component (MPC) parameters and to identify path "births" and "deaths." In Section IV, a novel wideband dynamic directional indoor channel model is proposed based on the Markov process. Section V presents the results from an extensive analysis of the measurement data. Section VI describes the power and spatio-temporal variations of paths within their lifespans. Section VII summarizes the implementation procedure of the channel model. In Section VIII, the performance of the proposed channel model is evaluated by comparing the statistical behavior of the measurement results with the simulations results. Finally, in Section IX, appropriate conclusions are drawn.

II. MEASUREMENT SETUP AND ENVIRONMENTS

A. Measurement Setup

The single-input–multiple-output (SIMO) measurements were conducted using a Medav RUSK BRI channel sounder operating at 5.2 GHz with an effective dynamic range of 40 dB [7]. A periodic multitone signal with a bandwidth of 120 MHz and repetition period of 0.8 μ s was employed. The frequency domain channel response was calculated online and stored on the sounder's hard disk for post-processing. The mobile transmitter (TX) used an omnidirectional antenna transmitting at an input

power of +26 dBm with a stationary receiver (RX) comprising a uniform linear array (ULA). The ULA had eight active dipolelike elements spaced by half a wavelength and two dummy elements at both ends to balance the mutual coupling effect. The effective azimuth visible range of the ULA was 120° .

The dynamic measurements were conducted by slowly pushing the TX towards the RX using a trolley and wireless telemetry equipment specially developed for this dynamic channel sounding exercise. The trolley had two odometers on the left and right wheels that enable precise logging of the distance moved. The sounder was configured to record 20 SIMO snapshots consecutively for every 80 mm moved, where a SIMO snapshot consists of eight complex channel response measurements in the frequency domain across the eight-element ULA. For a multitone signal period of 0.8 μ s, the time for recording a full SIMO snapshot was 12.8 μ s [7]. Therefore, the total recording time of one fast Doppler block (FDB) was 256 μ s, which was well within the coherence time of the channel and also the 2-ms medium access control (MAC) frame of the HIPERLAN/2 standard. A FDB in this measurement consists of a block of 20 consecutive SIMO snapshots. Since the trolley was pushed at approximately 1 m s^{-1} , the distance moved when one SIMO snapshot was being recorded was $2.22 \times 10^{-4} \lambda$ (0.02% of λ). Therefore, the uncertainty introduced by the trolley movement in one SIMO snapshot was negligible.

B. Measurement Environments

The dynamic measurements were conducted in a modern office environment. The office environment was highly cluttered, where standard office furniture, wooden shelves (height 1.83 m), and metal cabinets (height 1.3/1.85 m) were present. The tables were partitioned with soft boards (height 1.3/1.5 m). The floor was carpeted and the walls were made of bricks and concrete. A number of different measurements were taken in this environment as well as other typical indoor scenarios such as different types of corridors and a large open space. Full details of all of the conducted measurement scenarios are given in [8]. For brevity, this paper only describes the measurements, shown in Fig. 1, used in the data analysis presented in the following sections. However, other measurements confirm results reported in this paper. The mobile TX was pushed along the dotted path (about 16 m) and RX was fixed at a position labeled as "RX." The height of the mobile TX was fixed at 1.8 m, while the height of the stationary RX was fixed at 2.1 m. The arrow indicates the orientation of the ULA broadside direction. In order to obtain the 360° full spatial view of the radio channel, three different RX orientations $(0^{\circ}, 120^{\circ}, \text{ and } 240^{\circ})$ were used during the measurements (see Fig. 1). The measurements at this location were conducted during out of office hours with minimal human perturbation. However, most measurements in all other scenarios were conducted during normal office hours with no restrictions imposed on the channel as people were free to move.

III. DYNAMIC DATA ANALYSIS AND PROCESSING

In order to aid the development of the channel model, the required channel parameters were extracted and analyzed from



Fig. 1. Sketched plans of the office environment.

the data collected from the measurement campaign described above. In general, the data analysis procedure can be classified into two stages: multipath channel parameter estimation and identification of path "birth" and "death."

A. Multipath Channel Parameter Estimation

The super-resolution frequency domain space-alternating generalized expectation maximization (FD-SAGE) algorithm is used to detect and estimate the required multipath channel parameters such as the number of MPCs, their complex path gains, time of arrivals (TOAs), and angle of arrivals (AOAs) [9]. Since the total time to record 20 SIMO snapshots (or one FDB) is well within the coherence time of the channel, averaging can be carried out across a FDB (i.e., averaging a block of 20 SIMO snapshots) in order to enhance the signal-to-noise ratio before using the FD-SAGE algorithm to estimate the required parameters. As the trolley was in motion when the channel was being captured, paths can appear and remain for a certain time before finally disappearing. Hence, this contributes to a set of channel parameters that varies as a function of FDB. Strictly speaking, the channel parameters vary as a function of MT displacement. Since the FDB index, n corresponds to the MT displacement whereby one FDB is equivalent to 80 mm, for simplicity, the authors refer the dynamic statistics described herein as a function of FDB index. The total number of FDBs, N varies according to the total distance traveled by the trolley. Thus, N is a dimensionless positive integer with typical values in the 500-850 range (as a direct consequence of the dynamic measurement settings [8]) depending on the environment under consideration.



Fig. 2. (a) The concept of *active path* and *active region*. (b) The concept of *uncertainty region*.

B. Identification of Path "Birth" and "Death"

Two important parameters that form the basis of the dynamic channel modeling are the number of path "births" and "deaths" at any time instant, throughout the whole measurement run. By knowing these two parameters, the lifespan of each of the propagation paths can be derived. The total number of active paths, $L_{\rm T}$, in each particular FDB can be classified into new and inherited paths. New paths or births are defined as paths that first appear in that particular FDB, while inherited paths are defined as paths that existed in the previous FDB. Inherited paths can be further divided into two subcategories, i.e., alive and dead paths; alive paths are paths whose lifespan continues into the following FDB, while dead paths are paths that end their lifespans in that particular FDB.

In order to identify the number of births, $L_{\rm B}$, and deaths, $L_{\rm D}$, in each FDB, we propose a novel data analysis method where we introduce the terms *active path* (AP), *active region* (AR), and *uncertainty region* (UR). The area of the AR is determined by the intrinsic temporal and angular resolution of the measurement system, namely the *Rayleigh resolution* [10]. Here, the temporal and spatial coverage area of the AR is set to be $\tau_{\rm A} \pm \delta \tau$ and $u_{\rm A} \pm \delta u$, respectively, where $\tau_{\rm A}$ and $u_{\rm A}$ (the spatial domain here is expressed in *u*-space, defined as $u = \sin \phi$) form the centroid of the AR, while $\delta \tau$ and δu are chosen to be 9 ns and 0.25, respectively (see the Appendix for justification). Fig. 2(a) illustrates the concept of AP and AR.

Due to the limited resolution of the measurement system and finite point-source modeling errors in the FD-SAGE algorithm [9] when used in a distributed-source environment (i.e., in the presence of clusters of closely spaced multipaths), the estimated spatial-temporal parameters corresponding to a particular cluster of rays will correspond to the nominal parameter values within the cluster. Note that this observation is valid when the spatial-temporal extent of the cluster is smaller than the spatial-temporal *Rayleigh resolution* of the measurement system. Since the superposition of the paths within the cluster exhibits a fast-fading phenomena (in terms of resultant complex path gain of the cluster), the estimated parameter values will exhibit a finite fluctuation from one FDB to the next. The fluctuation here refers to a small deviation of the estimated parameter value from the previous one (within a very small MT displacement), as well as a sudden appearance or disappearance of a particular multipath that should have been detected with an ideal measurement system of infinite resolution. The temporary disappearance of these paths may be due to the fact that they are in a deep fade position, i.e., a null in the resultant complex path gain of the cluster. Thus, if paths appear, disappear, and reappear within a finite local region, they can still be assumed to be within their lifespans. As the angular resolution, δu , is 0.25, Jakes fading model cannot be applied to determine the distance between fades. Viewing the data reveals that fades can be of the order of 2λ ; hence, we can conclude that only paths in which their TOAs and AOAs do not vary more than ± 9 ns and ± 0.25 in the temporal and spatial *u*-space domains, respectively, up to three successive wavelengths are considered to be within their lifespans. Therefore, the UR is set equal to 3λ in order to account for the effect of fast-fading effects due to irresolvable closely spaced paths within a cluster, and finite fluctuations of the estimated parameter values within a local region of 3λ . Any paths that appear beyond the UR are considered to be the birth of some new paths. Fig. 2(b) illustrates the concept of the UR in identifying the "birth" and "death" of a path.

IV. DYNAMIC CHANNEL MODELING APPROACH

A new wideband stochastic indoor propagation channel model that incorporates both the spatial and temporal domains as well as the dynamic evolution of paths is proposed. Analysis of the measurement data showed that MPCs tend to form clusters in the spatio-temporal domains. Furthermore, correlation was also observed in these two domains [11]. As a result, a wideband channel model that incorporates both the clustering and correlation effects was proposed in [12]. However, this model does not incorporate the dynamic evolution of paths but assumes that the channel is quasi-static. In this paper, we extend the clustering spatio-temporal channel model described above to include the dynamic properties of the channel so that the model will have the capability to track the paths when the MT moves.

The dynamic directional channel model can be characterized by the distance-variant directional channel impulse response

$$h(n;\tau,\phi) = \sum_{l=1}^{L_{\mathrm{T}}(n)} \alpha_l(n) \cdot \delta\left[\tau - \tau_l(n), \phi - \phi_l(n)\right] \quad (1)$$

for n = 1, ..., N, where $\delta(\cdot)$ is the Dirac delta function, $L_{\rm T}(n)$ is the total number of active paths in the *n*th FDB, while $\alpha_l(n)$, $\tau_l(n)$, and $\phi_l(n)$ are the complex path gain, TOA, and AOA of the *l*th path in the *n*th FDB, respectively. It has been reported in [12] that $L_{\rm T}$ can be well modeled by an exponential pdf while

 $\{\tau_l\}_{l \in L_T(n)}$ and $\{\phi_l\}_{l \in L_T(n)}$ are modeled by a two-dimensional joint pdf given by

$$f(\tau_l, \phi_l) = f(\phi_l | \tau_l) \cdot f(\tau_l) \tag{2}$$

where $f(\phi_l | \tau_l)$ is the Gaussian conditional AOA pdf in which the standard deviation varies as a function of TOA, which can be approximated by a Weibull distribution. Note that (2) is applicable under the LOS scenario because under the obstructed LOS (OLOS) and non-LOS (NLOS) scenarios, a simplification can be made to (2) with $f(\tau_l, \phi_l) = f(\phi_l) \cdot f(\tau_l)$ where $f(\phi_l)$ and $f(\tau_l)$ are the marginal AOA and TOA pdf, respectively. In [12], it was reported that $f(\tau_l)$ can be modeled by an exponential pdf and $f(\phi_l)$ was approximately uniform over $[0^{\circ}, 360^{\circ}]$. While $\{\alpha_l\}_{l \in L_T(n)}$ is assumed to be an independent complex Gaussian process.

A. An M-Step, 4-State Markov Channel Model

Initially, both Markov and non-Markov models were used to investigate the dynamic behavior of the channel. Analysis results show that the non-Markov model is inferior to the Markov model. This implies that the channel incorporates memory. Hence, a Markov model will be adapted to model the dynamic properties of the channel. Here, a 4-state Markov channel model (MCM) is proposed in order to model the dynamic evolution of paths when the MT in motion, where each state is defined as follows:

- S_0 —no "birth" or "death" (B_0D_0);
- S_1 —one "death" only (B_0D_1) ;
- S_2 —one "birth" only (B_1D_0) ;
- S₃—one "birth" and one "death" (B₁D₁).

Note that four states are required in order to account for the correlation that exists between $L_{\rm B}$ and $L_{\rm D}$. The validity of this observation is confirmed by results obtained from the measurement data from all of the investigated environments, which will be presented in the following section. Fig. 3 illustrates the state transition diagram of the 4-state MCM.

The probabilistic switching process between states in the channel model is controlled by the state transition probability matrix \mathbf{P} given by

$$\mathbf{P} = \{p_{ij}\} = \begin{pmatrix} p_{00} & p_{01} & p_{02} & p_{03} \\ p_{10} & p_{11} & p_{12} & p_{13} \\ p_{20} & p_{21} & p_{22} & p_{23} \\ p_{30} & p_{31} & p_{32} & p_{33} \end{pmatrix}$$
(3)

where *i* and *j* denote the state index, while p_{ij} is the state probability that a process currently in state *i* will occupy state *j* after its next transition. Note that p_{ij} must satisfy the following requirement:

$$0 \le p_{ij} \le 1, \qquad 1 \le i, \ j \le K - 1$$
 (4)

$$\sum_{j=0}^{K-1} p_{ij} = 1, \qquad i = 0, 1, \dots, K-1$$
 (5)

where K is the number of states, i.e., K = 4 in our case. P describes how paths appear and disappear when the MT moves.



Fig. 3. State transition diagram of the 4-state Markov channel model.

The total distance traveled by the MT can be divided into N FDBs. Analysis of the measurement data shows that, at any instant, as the MT moves from one FDB to another, i.e., from the *n*th to (n + 1)th FDB, multiple births and deaths can occur within one FDB. This implies that the standard 4-state MCM described above is insufficient as it will only allow a single event per transition. In order to account for the multiple events case, a multiple step (M-step) MCM is proposed. Hence, by applying the M-step 4-state MCM, both the correlation between $L_{\rm B}$ and $L_{\rm D}$ as well as the multiple births and deaths will be taken into consideration. The number of steps M is determined by the maximum number of births, $L_{\rm B,Max}$, and maximum number of deaths, $L_{\rm D,Max}$, for a particular measurement file.

B. Markov Channel Model Parameter Estimation

Each measurement route might exhibit several propagation modes (both LOS and NLOS) when the MT moves along the trajectory even though these routes are from the same environment. Thus, due to the distinction in the B–D statistics and the spatio-temporal dispersion and correlation properties for LOS and NLOS scenarios, the model is generalized and parameterized by classification of measurement runs into sections with a similar propagation mechanism [13]. In order to estimate the parameters of the MCM, i.e., elements of **P** from the measurement data, the following procedure is applied to each classified measurement section.

- 1) Determine the value of M according to $L_{\rm B,Max}$ and $L_{\rm D,Max}$.
- 2) Extract the B–D probability matrix \mathbf{A} , which is an $(M + 1) \times (M + 1)$ square matrix. Elements of \mathbf{A} represent the probability of p and q number of birth and death paths, respectively, of a particular measurement section. Note that the matrix dimension of \mathbf{A} is purely dependent on the value of M. An example of \mathbf{A} for M = 4 is given by

$$\mathbf{A} = \{a_{pq}\} = \overbrace{\begin{pmatrix}a_{00} & a_{01} & a_{02} & a_{03} & a_{04}\\a_{10} & a_{11} & a_{12} & a_{13} & a_{14}\\a_{20} & a_{21} & a_{22} & a_{23} & a_{24}\\a_{30} & a_{31} & a_{32} & a_{33} & a_{34}\\a_{40} & a_{41} & a_{42} & a_{43} & a_{44}\end{pmatrix}}_{= 0, 1, \dots, 4} L_{\mathrm{D}}$$
(6)

where the number of columns and rows represents the number of births and deaths that can occur within one FDB.

- 3) Set up the $[(M + 1)^2 + 4]$ nonlinear equations in order to estimate all elements of **P**. $(M + 1)^2$ equations relate a_{pq} to products of p_{ij} . For example, $a_{00} = p_{00}^M$; $a_{01} = p_{00}^{M-1}p_{01} + (M 1)p_{00}^{M-2}p_{01}p_{10}$; etc. The four additional equations are due to the Markovian property in which the entries in **P** must satisfy the requirement imposed by (5). For a 4-state MCM, **P** consists of 16 variables that need to be estimated. For cases when $M \ge 3$, this becomes an overdetermined system where the number of equations is more than the number of variables to be estimated. After forming the required equations, all variables are estimated using a nonlinear least squares optimization method [14]. Here, the subspace trust region method based on the interior-reflective Newton algorithm as described in [15] is deployed.
- The interior-reflective Newton algorithm used in this (4)paper solves the system by assuming that the solution has a small or zero residual. If the residual is relatively large, this method will be slow or may start to diverge. Furthermore, due to the large number of variables to be estimated, we propose to run the optimization problem several times (say 100) with different sets of randomly chosen initial conditions in order to find a better minimum and to increase the likelihood that the estimated parameters converge to the desired global minimum. Hence, the parameter set that minimizes the sum-of-squared-errors (i.e., with the lowest function value) will be chosen as the state transition probabilities of the particular measurement file. By employing the "evolutionary approach" whereby a problem with a smaller number of independent variables is solved first can also improve the chances of finding the global minimum. In this approach, solutions from lower order problems are used as starting points for higher order problems by using an appropriate mapping [14].

Analysis results reported in [13] show that the MCM can be generalized by several sets of transition probability matrices, i.e., $\mathbf{P}_{\mathrm{LOS}}$ as $\mathbf{P}_{\mathrm{NLOS}}$ for LOS and NLOS scenarios, respectively. This enables the B–D statistics to be generated

	Averaş	ge P _{LOS}		Average P _{NLOS}							
(0.9039	0.0280	0.0367	0.0272)		0.9911	0.0029	0.0020	0.0018)			
0.0000	0.5029	0.0000	0.4972		0.0000	0.8869	0.0001	0.1131			
0.0000	0.0000	0.1663	0.8340		0.0000	0.0000	0.5286	0.4715			
0.0000	0.3064	0.4165	0.2772		0.0000	0.0000	0.9588	0.0411			

TABLE ~~I Average Values of the ${\bf P}_{\rm LOS}$ and ${\bf P}_{\rm NLOS}$ in the Office Environment

according to the classified sections. Table I lists the average values of the $\mathbf{P}_{\mathrm{LOS}}$ and $\mathbf{P}_{\mathrm{NLOS}}$ for the office environment. Average values for all other investigated environments such as a large open space and corridors are reported in [13]. These parameters obtained are useful for Monte Carlo simulations of the channel model.

V. MEASUREMENT RESULTS

In this section, we present some measurement results in order to validate the modeling concept described above. Due to the similarity in the statistical behavior of all of the investigated environments, unless otherwise stated, all measurement results presented here correspond to the office environment described in Section II. Fig. 4 shows the distance-variant power-delay density spectrum (DV-PDDS) and the distance-variant powerazimuth density spectrum (DV-PADS) for a sample measurement file with the measurement configuration as described in Section II. The DV-PDDS shows that the TOA of the strongest LOS component increases as the trolley moves along its trajectory, corresponding to the trolley moving away from the RX. Also observable in the graph are the higher order reflections. The major first-order reflection is due to the reflection off the wall with the entrance door. This accounts for the decrease in TOA as the trolley moves farther away from the RX. On the other hand, the major second-order reflection is due to the signal being first reflected by the wall behind the RX (first order), and then reflected again by the wall with the entrance door (second order) before arriving at the RX. The DV-PADS further substantiates the following observations. As can be clearly seen, the LOS component changes its AOA from $+60^{\circ}$ to 0° as the trolley moves away from the RX, while both the first- and second-order reflections have AOAs at approximately 0°. These graphs also reveal that with passing time, paths appear and disappear. Therefore, $L_{\rm T}$ varies with the distance moved by the trolley as illustrated in Fig. 5(a). In general, larger values of $L_{\rm B}$ and $L_{\rm D}$ were obtained for the OLOS and NLOS scenarios when compared to the LOS scenario. This is mainly due to a larger $L_{\rm T}$ for OLOS and NLOS scenarios. The presence of a LOS path causes the channel sounder to miss paths with relatively low powers as the dynamic range of the channel sounder is finite. As diffuse reflections dominate in the OLOS and NLOS scenarios, strong paths detected by the channel sounder have approximately the same power. Therefore, paths with relatively low power can still



Fig. 4. (a) Distance-variant power-delay density spectrum (DV-PDDS) and (b) distance-variant power-azimuth density spectrum (DV-PADS) in the office environment.

be detected by the channel sounder provided they fall within the dynamic range.

Here, we are interested in the variation of $L_{\rm B}$ and $L_{\rm D}$ as the trolley moves. Analysis of the measurement data indicated that a correlation exists between $L_{\rm B}$ and $L_{\rm D}$. Fig. 6 shows the dynamic evolution of $L_{\rm B}$ and $L_{\rm D}$ as the trolley moves along its trajectory for the same measurement file used in Fig. 4. It is obvious that the variation pattern of $L_{\rm B}$ and $L_{\rm D}$ is very similar. The B–D correlation coefficient, $\rho_{\rm BD}$, between $L_{\rm B}$



Fig. 5. Dynamic evolution of the total number of active paths $L_{\rm T}$ obtained from the (a) real-time office environment and (b) simulations results.

and $L_{\rm D}$ is calculated for each measurement file and is defined as follows:

$$\rho_{\rm BD} = \left| \frac{\sum_{n=1}^{N} \left(L_{\rm B}(n) - \bar{L}_{\rm B} \right) \left(L_{\rm D}(n) - \bar{L}_{\rm D} \right)}{\sqrt{\sum_{n=1}^{N} \left(L_{\rm B}(n) - \bar{L}_{\rm B} \right)^2 \sum_{n=1}^{N} \left(L_{\rm D}(n) - \bar{L}_{\rm D} \right)^2}} \right|,$$

$$\rho_{\rm BD} \in [0, 1] \quad (7)$$

where $L_{\rm B}(n)$ and $L_{\rm D}(n)$ are the number of births and deaths of paths in the *n*th FDB, respectively, while $\bar{L}_{\rm B}$ and $\bar{L}_{\rm D}$ are the mean number of births and deaths, respectively. On the average, $\rho_{\rm BD} > 0.75$ was obtained for all investigated environments, which clearly shows that a high correlation exists between $L_{\rm B}$ and $L_{\rm D}$. Thus, in order to generate a more realistic simulation model, the correlation must be taken into consideration. Fig. 7 shows an example of a joint pdf of $L_{\rm B}$ and $L_{\rm D}$, $f(L_{\rm B}, L_{\rm D})$, for a post-processed measurement data in an office environment where high probability was observed particularly for low values of $L_{\rm B}$ and $L_{\rm D}$. The correlation that exists between $L_{\rm B}$ and $L_{\rm D}$ might be due to the highly cluttered environment, where many reflections are subject to the blocking and unblocking of paths as the trolley moves along its trajectory.

The lifespan of a path, l_l , is the distance for which the path exists from its first appearance until it finally disappears as the MT moves along its trajectory and can be derived by knowing when the path was born and died. Hence, l_l is a random variable (RV) that can be described by a pdf. Note that l_l is as a function of the FDB index n, and thus, is dimensionless. Here, we found that the pdf of the path lifespan, $f(l_l)$, is best described by an exponential distribution as shown in Fig. 8(a).

As described in Section IV, the value of M is determined by $L_{B,Max}$ and $L_{D,Max}$. Another significant observation is that the values of $L_{\rm B}$ and $L_{\rm D}$ (hence, $L_{\rm B,Max}$ and $L_{\rm D,Max}$) are highly dependent on the presence of a LOS path. Under the LOS condition. M = 3 is sufficient, while for the OLOS and NLOS cases, at least M = 8 is required in order to ensure that P converges. These values were verified by simulation results by increasing M until the value of \mathbf{P} did not change significantly. For example, under the LOS condition, it was observed that all elements of \mathbf{P} estimated at M = 3 and M =4 (i.e., P_3 and P_4 , respectively) do not vary by more than 15%. Further increase in M would not alter the value of \mathbf{P} significantly. Thus, M = 3 is used as the upper limit of the step size to generate P for the LOS case. Generally, larger values of M correspond to environments with a larger number of paths.

VI. POWER AND SPATIO-TEMPORAL VARIATIONS WITHIN PATH LIFESPAN

A. Spatio-Temporal Variation Within Path Lifespan

As the MT moves along its trajectory, fluctuations in the path TOA and AOA occur within the path lifespan, l_l . Results from the data analysis reveal that the spatio-temporal variation of a particular path can be modeled by a linear polynomial approximation. Thus, linear least squares regression is used to find the best line fit through all data points of each path in the form of y = kx + b. Fig. 9 shows an example of the TOA-AOA fluctuations of paths within their lifespans. Note that paths with a lifespan of less than three FDBs are too short for analysis. Also in the figure is an illustration of the best line fit for each of these paths. It indicates that the direction of change is independent of the location on the spatio-temporal domain. Thus, the gradient k of each straight line can be described by an RV. Since vertical lines have an infinite value of k, the term spatio-temporal vector, ω is introduced and is defined as the acute angle between the TOA-AOA axes, where $w = \tan^{-1}(k)$. Therefore, ω is also an RV that can be described by a pdf. Here, we found that $f(\omega)$ can be well modeled by a Gaussian pdf as illustrated by the inner plot in Fig. 9.

B. Power Variation Within Path Lifespan

Power variation of a path occurs due to movement of the MT. To date, most researchers assume that the power variation of a



Fig. 6. Dynamic evolution of the number of births $L_{\rm B}$ and deaths $L_{\rm D}$ in the office environment.



Fig. 7. Joint pdf of $L_{\rm B}$ and $L_{\rm D}$, $f(L_{\rm B}, L_{\rm D})$, obtained from the real-time office environment.

path within its lifespan can be described by a smooth monotone transition function [16]–[18]. This transition function was first proposed in [19], where power was assumed to vary as a sinusoidal function in the region where the path appears and disappears. The main reason for making the following assumption is to exclude the abrupt changes of power variation. However, this conjecture was made without any physical propagation reasoning or supported by any measurement results.

In order to model the power variation of a path within its lifespan, its power spectral density (PSD) is studied to determine an appropriate filter that is able to reproduce a set of random signals that exhibit similar spectral characteristics. Paths with a relatively long lifespan are focused on as they can be used for spectral estimation. Paths with a long lifespan are caused by the same superstructure (e.g., furniture, walls, doors, etc.) forming the path during the whole measurement run. However, due to the measurement constraints, the data obtained from the measurements have an uneven distance spacing. A straightforward approach is to reconstruct evenly spaced data using interpolation or rebinning before applying the conventional discrete Fourier transform (DFT) or fast Fourier transform (FFT) methods. However, both interpolation and rebinning perform poorly and introduce significant distortion in the spectral density of the analyzed data. Furthermore, the DFT and FFT methods perform well only when the data size is relatively large. In order to mitigate this effect, a method suitable for unevenly sampled and relatively short signals, the Lomb-Scargle periodogram (LSP) [20] is deployed. The LSP is based on a local least squares fit of the data by sinusoids centered on each data point of the distance-series (equivalently



Fig. 8. The pdf of the path lifespan $f(l_l)$ obtained from the (a) real-time office environment and (b) simulations results.

time-series) data [21], [22]. Given an unevenly spaced signal, $h_n \equiv h(x_n)$, where n = 1, 2, ..., N, the normalized LSP $P_N(\psi)$ is given as follows [20]:

$$P_{N}(\psi) = \frac{1}{2\sigma^{2}} \left\{ \frac{\left[\sum_{n=1}^{N} (h_{n} - \bar{h}) \cos \psi(x_{n} - \eta)\right]^{2}}{\sum_{n=1}^{N} \cos^{2} \psi(x_{n} - \eta)} + \frac{\left[\sum_{n=1}^{N} (h_{n} - \bar{h}) \sin \psi(x_{n} - \eta)\right]^{2}}{\sum_{n=1}^{N} \sin^{2} \psi(x_{n} - \eta)} \right\}$$
(8)

where \bar{h} and σ^2 are the mean and variance of the data, respectively, while η is defined by

$$\tan(2\psi\eta) = \frac{\sum_{n=1}^{N} \sin 2\psi x_n}{\sum_{n=1}^{N} \cos 2\psi x_n}.$$
(9)

Due to its local least squares fit nature, the LSP works equally well for unevenly spaced sampled data. Furthermore, it is also much less prone to aliasing distortions in small size data sets.

Fig. 10(a) and (b) illustrates the power variation of a path within its lifespan and its corresponding PSD (in logarithmic scale), respectively. This *active path* is chosen randomly from the same measurement file used to plot previous figures (i.e., Figs. 4–9). These figures show that only low-frequency components are significant. Several other paths were also investigated and similar PSDs were observed. This implies that the power variation of a path within its lifespan can be well modeled by a simple LPF, which exhibits a similar frequency response. The results obtained here give an insight to a more realistic representation of the shape transition function as compared to the sinusoidal function assumed by previous researchers.

Generally, the power variation of a path within its lifespan can be caused by several mechanisms. Firstly, due to the motion of the MT along its trajectory that changes the reflection coefficients of some media. For example, as the trolley moves along the trajectory in the office environment, reflections can be due to the walls, furniture, doors, or even people in the surroundings. Thus, the building structure can cause a path to fade within its lifespan. Secondly, due to the finite spatiotemporal resolution of the measurement system, paths with closely spaced TOAs and AOAs are unable to be resolved. This causes multiple paths being detected as "a single path." From the physical propagation mechanism point of view, rough surface scattering can lead to more than one reflected components with closely spaced TOAs and AOAs due to different angles of reflections. Paths reflected from rough surfaces can combine coherently or incoherently depending on their relative path length. As a result, a variation in amplitude or power can occur within the lifespan of a particular path, i.e., the same propagation path can fade within its lifespan as illustrated in Fig. 10(a).

VII. IMPLEMENTATION OF THE CHANNEL MODEL

In this section, the implementation of the proposed MCM is summarized with reference to the flowchart depicted in Fig. 11. Firstly, the user is required to provide input parameters such as the type of environment (e.g., office) and scenario (e.g., LOS or NLOS) to be simulated. Dependent on these, the appropriate transition probability matrices, P_{LOS} and P_{NLOS} (see Table I), and the number of steps M will be chosen as the simulation parameters. Also, the distance traveled (i.e., the total number of FDB N) must also be provided as part of the input parameters. During the initialization stage, both $L_{\rm B}(1)$ and $L_{\rm D}(1)$ are initialized to zero and the model generates the total number of active paths in the first FDB, $L_{\rm T}(1)$, according to the exponential pdf, $f(L_{\rm T})$, as proposed in [12]. Following this, the clustering spatio-temporal channel model as proposed in [12] is adopted in order to generate the new paths' powers, $|\alpha_l|^2(n)$, TOAs, $\tau_l(n)$, and AOAs, $\phi_l(n)$, for $l = 1, \ldots, L_T(n)$ and n = 1, ..., N. In order to incorporate the dynamic evolution of paths due to motion, i.e., the number of births, $L_{\rm B}(n)$, the number of deaths, $L_{\rm D}(n)$, and thus, the total number of active paths, $L_{\rm T}(n)$, in the *n*th FDB for $n = 1, \ldots, N$, the



Fig. 9. Example of the spatio-temporal variation of path within its lifespan in the office environment with the resulting Gaussian distributed *spatio-temporal* vector, ω .



Fig. 10. (a) Power variation of a randomly selected path within its lifespan and (b) its corresponding power spectral density from a sample data file obtained from the office environment.

M-step 4-state MCM is adopted in which $L_{\rm T}(n)$ can be computed as follows:

$$L_{\rm T}(n) = L_{\rm T}(n-1) + L_{\rm B}(n) - L_{\rm D}(n)$$
(10)

where $L_{\rm T}(n-1)$ is the total number of active paths in the previous FDB. Furthermore, the power and the spatio-temporal variations of a path within its lifespan are also incorporated as discussed in Section VI.

VIII. CHANNEL MODEL EVALUATION

The validity of the newly proposed stochastic channel model can be evaluated by comparing the key statistics of the simulation results with the measurement results. As the model is statistical, there is no one-to-one correspondence between simulation and measurement. In order to compare the proposed model with the measurements, an equivalent scenario was encoded into the model. Values generated through simulations were subjected to the same statistical analysis as the real measurement data in order to evaluate the similarity between them. Firstly, a comparison is made between the values of B-D probability matrix obtained from the measurement data A with the one obtained through simulation, A'. Simulation results show that a reasonable match is obtained between A and A' in which the B–D probability matrix error $\varepsilon_{\mathbf{A}}$ (i.e., $\varepsilon_{\mathbf{A}} = |\mathbf{A} - \mathbf{A}'| \times 100\%$) is less than 3% per element with the sum-of-errors less than 20% for all environments under consideration. Table II displays the results for three examples of this comparison by considering the LOS condition where M = 3. Secondly, the comparison has been performed for the total number of active paths $L_{\rm T}$ over the whole measurement run as shown in Fig. 5(a) and (b) for the measurement and simulation results, respectively. These two figures clearly show that the variation of $L_{\rm T}$ obtained through simulation agrees well with the measurement results, where the simulated $L_{\rm T}$ is shown to be bounded within the



Fig. 11. Flowchart for the implementation of the proposed wideband dynamic directional Markov channel model.

Number	Real B–D Probability Matrix, A				Simulated B–D Probability Matrix, A'					B–D Probability Matrix Error, $\varepsilon_{\mathbf{A}}$					
1	(0.0429	0.0858	0.0456	0.0268)	0.0498	0.0761	0.0599	0.0217)		(0.69%	0.97%	1.43%	0.51%)	
	0.0643	0.0912	0.0992	0.0563	0.0577	0.0914	0.1004	0.0442		0.66%	0.02%	0.12%	1.21%	0.0007	
	0.0456	0.0831	0.0885	0.0536	0.0554	0.0830	0.0892	0.0619		0.98%	0.01%	0.07%	0.83%	= 8.69%	
	0.0402	0.0483	0.0617	0.0670	0.0331	0.0503	0.0611	0.0648		0.71%	0.20%	0.06%	0.22%		
2	(0.0602	0.0843	0.0410	0.0313)	0.0611	0.0777	0.0594	0.0231)		(0.09%	0.66%	1.84%	0.82%)		
	0.0747	0.1349	0.0940	0.0578	0.0825	0.1274	0.1048	0.0331		0.78%	0.75%	1.08%	2.47%	10.000	
	0.0723	0.0940	0.0506	0.0361	0.0704	0.0887	0.0715	0.0341		0.19%	0.53%	2.09%	0.20%	= 13.39%	
	0.0265	0.0530	0.0506	0.0386	0.0347	0.0493	0.0504	0.0318		0.82%	0.37%	0.02%	0.68%		
3	(0.0279	0.0529	0.0418	0.0306)	(0.0308	0.0463	0.0486	0.0302)		(0.29%	0.66%	0.68%	0.04%)	
	0.0418	0.0919	0.1003	0.0446	0.0415	0.0929	0.0993	0.0380		0.03%	0.10%	0.10%	0.66%		
	0.0418	0.1142	0.1058	0.0529	0.0418	0.1136	0.1077	0.0571		0.00%	0.06%	0.19%	0.42%	= 3.48%	
	0.0334	0.0557	0.1031	0.0613	0.0339	0.0558	0.1026	0.0599		0.05%	0.01%	0.05%	0.14%		

TABLE $\,$ II Comparison Between the Real and Simulated B–D Probability Matrix (M=3)



Fig. 12. Example of the simulated spatio-temporal variation of path within its lifespan.

lower and upper limit of $L_{\rm T}$ obtained from the measurements. The proposed model is further evaluated by looking at the pdf of the path lifespan $f(l_l)$ and the spatio-temporal variation of a path within its lifespan for both measurement and simulation results. Fig. 8(a) and (b) shows $f(l_l)$ obtained from the measurement and simulation results, respectively, whereboth were well modeled by an exponential pdf. Finally, Fig. 12 illustrates the simulated spatio-temporal variation of a path within its lifespan. This graph clearly shows that its variation pattern is very similar to that of Fig. 9.

IX. CONCLUSION

A novel stochastic wideband dynamic directional indoor channel model has been proposed based on real-time dynamic measurement data collected at 5.2 GHz in several typical indoor environments. The proposed model incorporates both the spatial and temporal domain properties as well as the dynamic evolution of paths when the MT is in motion, based on the concept of a Markov process. The super-resolution FD-SAGE algorithm was deployed to extract the MPC parameters prior to identification of path "birth" and "death" using a new data analysis technique. The resolution achieved by deploying these data analysis methods is far greater than the resolution limit of current indoor wireless systems such as HIPERLAN/2 and IEEE802.11a. While consumer technology specifications are below that of the sounder, the parameters given will be valid for the environments described.

A detailed analysis of the measurement data shows that a correlation exists between the number of births and deaths.

Furthermore, multiple births and deaths are also plausible at any time instant. The main contribution of the paper is the introduction of an M-step 4-state MCM that will take into account multiple births and deaths as well as the B-D correlation. Such an approach has not previously been considered in detail as most research have assumed that the channel is quasistatic and the births and deaths are due to two separate stochastic processes. By knowing the birth and death of a path, the path lifespan is derived, which has been shown to be well modeled by an exponential pdf. The power and spatiotemporal variations of each path within their lifespans were also investigated. The spatio-temporal variation can be completely described by a single parameter called the spatio-temporal vector, ω , which describes the changes in the temporal and angular domains of a particular path within its lifespan which was found to be well modeled by a Gaussian pdf. The PSD obtained using the LSP shows that the power variation can be modeled by a simple LPF. In addition, the method used to extract the MCM parameters from the experimental data was also discussed. Due to the distinction in the B-D statistics, spatio-temporal dispersion and correlation properties for different propagation scenarios, the model is generalized by segmentation of the measurement runs into sections with the same propagation mode. Here, it was found that the model is completely parameterized by several sets of transition probability matrices associated with the type of environment and scenario under consideration.

The new model was implemented and evaluated by comparing the key statistics of the simulation results with the measurement results such as the B–D probability matrix, the evolution of the total number of active paths, distribution of the path lifespan, and the spatio-temporal variation of a path within its lifespan. Since the channel model developed in this work is focused on the indoor WLAN application based around 5 GHz, the proposed model is most suitable for simulating any HIPERLAN/2 and IEEE802.11a systems that employ smart antenna architectures particularly for the performance evaluation of tracking algorithms, as well as for the evaluation of space–time processing applications in the indoor environment.

APPENDIX

The basic functionality and channel modeling concept of the Medav RUSK BRI channel sounder is described in [7]. Here, the sounding bandwidth was set to 120 MHz with a multitone period of 0.8 μ s. Since the measured data were stored in the complex frequency domain, it produces 97 frequency samples equally spaced at 1.25 MHz. Due to the limited sounding bandwidth, the energy of the impulse response in a singlesource scenario will be "spread" across the delay domain with its first null nearest to the main lobe given by $\pm 1/(N_f \Delta f)$, where N_f is the number of frequency samples and Δf is the frequency spacing between the samples. This determines the temporal Rayleigh resolution of the sounder $\delta \tau_{\rm Ray} = 1/(97 \times$ 1.25 MHz $\approx 8.25 \text{ ns.}$ Similarly, due to the limited spatial aperture of the eight-element ULA, its power-azimuth density spectrum for a single source is "spread" across the azimuth, with its first null nearest to its main lobe given by $\pm \lambda/(N_{\rm S}d)$,

where $N_{\rm S}$ is the number of antenna elements and d is the element spacing. Note that the null in the spatial domain is expressed in the *u*-space, where $u = \sin \phi$. The main reason that *u*-space is used here is to retain the linearity of spatial resolution of the ULA across the azimuth, i.e., the spatial resolution is a linear function of u, and a nonlinear function of ϕ . Hence, the spatial *Rayleigh resolution* of the system (in *u*-space) is given by $\delta u_{\rm Ray} = 0.25$ for an eight-element ULA with $\lambda/2$ element spacing. Based on the intrinsic resolution of the system, the spatial-temporal coverage area of the AR is set to be $u_{\rm A} \pm \delta u$ and $\tau_{\rm A} \pm \delta \tau$, respectively, where $\tau_{\rm A}$ and $u_{\rm A}$ represent the centroid of the AR, while $\delta \tau$ and δu are chosen to be 9 ns and 0.25, respectively.

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