A BLACK-BOX IDENTIFICATION FRAMEWORK FOR WIRELESS TERAHERTZ NETWORKS

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Abstract—This paper discusses the feasibility of wireless Terahertz communications links deployed in a metropolitan area and lays down a black-box system identification framework to model the large scale fading of such channels. The movement of the receiver is modeled in state space by an autonomous dynamic linear system whereas the geometric relations involved in the attenuation and multi-path propagation of the electric field are described by a static nonlinear mapping. A subspace algorithm in conjunction with polynomial regression is used to identify a Wiener model from time-domain measurements of the field intensity. The identification procedure is validated by using the model to perform predictions in a simulation involving direct line-of-sight propagation, ground and wall reflection as well as diffraction around a corner. The proposed algorithm is of interest to developers providing U.S. E-911 compliant solutions as well as Location-Based Services (LBS), such as turn-by-turn navigation, mobile resource and logistics management.

Keywords—System identification, telecommunications, Terahertz, subspace identification, Wiener systems.

1 Introduction

Nowadays, cheap high-bandwidth communications are in high demand owing to the increasing numbers of subscribers to bandwidth-hungry services, such as multimedia applications, in densely populated metropolitan areas. Such a demand has motivated the exploitation of higher carrier frequencies, which offer the further advantage that very compact antennae can be implemented for low transmit powers. In this context, further developments in the use of the THz gap for communications can be expected to occur in the near future.

Power-budget calculations (Mann, 2001), have shown that concerns over atmospheric absorption at THz frequencies are partly unfounded (Galvão et al., 2004). Such calculations show that it is possible to choose a fairly high carrier wave frequency and yet not suffer as much attenuation as that at much lower frequencies, and that for selected bands the total atmospheric absorption can be comparable to that experienced by systems currently being operated in the millimetre wave region.

Moreover, there is already a range of solutions at an advanced stage of development that could potentially open-up the THz gap for communications. Sources based on photomixing (Huggard et al., 2002), advances in push-pull electro-optic modulators and phase shifters in the Ka-band (26.5-36 GHz), as well as the V-band (46-56 GHz) (Zhang et al., 2001; Oh et al., 2001) and the potential for free-space to in-fibre all-optical interfacing (Fetterm an et al., 1998; Chang et al., 2002) are important technologies currently under development.

Finally, it is worth noting that the increasing interference between micro-cells in the present mobile network implementations is also a major source of concern. Such a problem is motivating research towards high frequency/bandwidth predominantly line of sight (LOS) solutions where the very high attenuation in the atmosphere can be utilised to facilitate frequency re-use.

In anticipation of these emerging solutions, the present paper discusses large scale fading models for line-of-sight THz wireless communications links taking into account the movement of the receiver.

The text is organized as follows. Section 2 describes the propagation scenario under consideration in this study. Section 3 presents a framework for predicting the large-scale fading behaviour of the electric field by using a Wiener system model. Section 4 presents the results of a simulation that illustrates the proposed framework. Concluding remarks and suggestions for further research are given in section 5.

2 A typical scenario for a wireless THz communications link

Fig. 1. Large scale fading static model of a typical emitter-receiver pair in a metropolitan area.
A direct line of sight ray $E_{LOS}$

$$E_{LOS} = \frac{E_0}{[(a - L \sin \theta)^2 + (a - L \cos \theta)^2]^{1/2} \times \exp(-j2\pi[(a - L \sin \theta)^2 + (a - L \cos \theta)^2]^{1/2} / \lambda)}$$

(1)

a ground reflected ray $E_{GR}$

$$E_{GR} = \frac{\Gamma_g E_0}{[(a - L \sin \theta)^2 + (a - L \cos \theta)^2 + 4h^2]^{1/2} \times \exp(-j2\pi[(a - L \sin \theta)^2 + (a - L \cos \theta)^2 + 4h^2]^{1/2} / \lambda)}$$

(2)

and a wall reflected ray $E_{WR}$

$$E_{WR} = \frac{\Gamma_w E_0}{[(a - L \cos \theta)^2 + (a + L \sin \theta)^2]^{1/2} \times \exp(-j2\pi[(a - L \cos \theta)^2 + (a + L \sin \theta)^2]^{1/2} / \lambda)}$$

(3)

where $E_0$ is a reference field intensity at unit distance from the transmitter and $\Gamma_g, \Gamma_w$ are the ground and wall reflection coefficients, respectively, given from the following Fresnel equations for parallel and perpendicular polarisation (to account for the fact that the wall is perpendicular to the ground):

$$\Gamma_g = \frac{\sqrt{e_{rg} - \cos^2 \phi_{rg} - e_{rg} \sin \phi_{rg}}}{e_{rg} \sin \phi_{rg} + \sqrt{e_{rg} - \cos^2 \phi_{rg}}}$$

(4)

$$\Gamma_w = \frac{\sin \phi_{rw} - \sqrt{e_{rw} - \cos^2 \phi_{rw}}}{\sin \phi_{rw} + \sqrt{e_{rw} - \cos^2 \phi_{rw}}}$$

(5)

where $e_{rg}$ and $e_{rw}$ are the complex dielectric constants of the ground and wall and $\phi_{rg}$ and $\phi_{rw}$ are the ground and wall incidence/reflection angles.

For simplicity, the diffraction gain behind the obstruction of height $h_o$ can be modelled by using the Fresnel-Kirchoff diffraction parameter:

$$v = h_o \sqrt{\frac{2(d_1 + d_2)}{\lambda d_1 d_2}$$

(6)

to define the diffraction gain (in dB) behind the obstruction:

$$\frac{E_D}{E_{LOS}} = F(v) = \frac{(1 + j)}{2} \int_{-\infty}^{\infty} \exp(-j\pi t^2 / 2) dt$$

(7)

with $E_{LOS}$ denoting the free space field strength in the absence of both the ground and the obstruction, $E_D$ being the diffracted field, and $F(v)$ being the complex Fresnel integral which is a function of the Fresnel-Kirchoff diffraction parameter $v$. An approximation of (7) was used (Rappaport, 1999). However, more elaborate methods for the modelling of diffraction based on the geometrical theory of diffraction (GTD) (e.g. Sarkar, 2003; McNamara et al., 1990; Luebbers, 1984) could also have been adopted.

The following section presents a framework for the prediction of large scale fading in this scenario, assuming a fixed transmitter and a moving receiver.

3 Proposed modelling framework

In the proposed approach, the movement of the receiver is described by an autonomous dynamic linear model of the form

$$x[k + 1] = Ax[k], x[0] = x_0$$

$$y[k] = cx[k]$$

(8)

where $x[k] = [x_1[k], x_2[k],... x_M[k]]^T$ is the vector of state variables at time index $k$, $A_{sys}$ is the state recursion matrix, $x_0 = [x_1[k_0], x_2[k_0],... x_M[k_0]]^T$ is the state vector at the initial time index $k_0$ and $y[k]$ is the output variable, which is linearly related to the states by the vector of weights $c$. As can be seen in Equations (1)-(3), the geometric relations involved in the attenuation and multipath propagation of the electric field are nonlinear static functions of the angular position $\theta$ and radius $L$. Thus, if the state variables in (8) are related to $\theta$ and $L$, the electric field intensity $E_s[k]$ at the receiver at time $k$ may be obtained as a nonlinear combination of $x_1[k], x_2[k],... x_M[k]$. In the current formulation, such a nonlinearity is approximated by a single-input mapping $G: \Re \rightarrow \Re, E_s[k] = G(y[k])$. This structure (Figure 2), in which the dynamics are linear and the static output function is nonlinear, is termed a Wiener system (Westwick and Verhaegen, 1996).

![Dynamic Linear Static Nonlinear](image)

Fig. 2. Wiener system formulation.

Small-scale spatial variation and time variation in transmitter intensity are not taken explicitly into account in the model. At millimeter wave frequencies, however, receiver micro-movements swamp the phase and the small-scale variation can be lumped with the receiver thermal noise into a single noise term after the nonlinear term of the model.

In this work, the nonlinear function $G$ will be approximated by a dominantly odd polynomial, that is

$$G(y) \approx \sum_{i=0}^{2M+1} p_i y^i, M \geq 0$$

(9)
In this framework, the identification problem can be stated as follows: Given a sequence of \( N \) measurements \( \{E[k], k = k_0, \ldots, k_0 + N - 1\} \), estimate the linear system matrices \( A, c, \) the initial state \( x_0 \) and the polynomial coefficients \( \{p_i, i = 0, \ldots, 2M + 1\} \). As shown in (Verhaegen and Westwick, 1995; Westwick and Verhaegen, 1996; Haverkamp et al., 1998; Lovera and Verhaegen, 1998; Lovera et al., 2000), estimates \( \hat{A}, \hat{c}, \hat{x}_0 \) can be obtained, up to a similarity and output scaling transformation, by using a MOESP (Multivariate Output-Error State Space) subspace algorithm (Overschee and Moor, 1996), as long as the nonlinearity is indeed dominantly odd. It is worth noting that in subspace algorithms, which perform a singular value decomposition as an intermediate step in the identification process, an appropriate model order can be obtained as the number of singular values significantly larger than zero (Overschee and Moor, 1996). From \( \hat{A}, \hat{c}, \hat{x}_0 \), an estimated sequence \( \{\hat{y}\} \) can be calculated and the polynomial coefficients \( p_i \) can be obtained by regressing the measured output \( \{E_i\} \) against \( \{\hat{y}\} \). The \( E_i \) and \( \hat{y} \) data can be mean-centered and scaled prior to regression in order to improve the numerical conditioning of the estimation.

The identification procedure can be validated by using the resulting model to perform \( q \)-step ahead predictions, that is to calculate

\[
\hat{E}_r(j + q | [j + 1, j]) = \sum_{i=0}^{2M+1} \hat{p}_{i,j-N+1} \hat{y}(j + q | [j + 1, j])
\]

where \( \hat{E}_r \) and \( \hat{y} \) denote predicted values of \( E_r \) and \( y \), respectively, whereas \( (j + q | [j + 1, j]) \) denotes that the prediction is carried out at instant \( k = j + q \) by using data acquired from \( k_0 = j + 1 \) up to \( k = j \). Moreover, \( \hat{p}_{i,j-N+1,j} \) denotes the estimate of the \( i \)-th polynomial coefficient obtained by using data acquired from \( k_0 = j - N + 1 \) up to \( k = j \). The predictions are performed on the basis of data acquired in a moving window of \( N \) points rather than using all the available data in order to make the model adaptive to changes in either the dynamics of the linear system or the nonlinearity \( G \). Moreover, in this manner, the assumption that the nonlinearity can be approximated by a dominantly odd polynomial only needs to be satisfied within the time frame comprising the identification window and the prediction horizon.

### 4 Simulation Results

The receiver motion was simulated in state space assuming a constant angular speed of \( 3\pi/20 \text{rad/s} \), and a radius \( L \) exponentially decaying from 10 m to 5 m, as depicted in Figure 3, using a sampling period \( T_s = 0.02 \text{s} \).

![Fig. 3. Trajectory of the receiver.](image)

In this example, the nonlinearity will be approximated as a 3rd order polynomial, i.e., \( M = 1 \). All simulations were carried out in the Matlab environment and the MOESP subspace implementation of the Matlab identification toolbox was employed in the linear modelling process.

Figure 4 shows the time evolution of the field intensity as the receiver moves in the trajectory shown in Figure 3. The intensity, which has been normalized to a maximum of one, initially increases as the receiver moves towards the transmitter and then decreases in a monotonic manner as the receiver moves away from the transmitter. The first discontinuity at 5 s is caused by the loss of the wall-reflected signal. The second discontinuity after 8 s occurs when the receiver enters the diffraction zone.

![Fig. 4. Field intensity at the receiver.](image)
corresponds to 30 sampling periods (20 points for the moving window and 10 points for the prediction).

The effect of measurement noise is illustrated in Figure 6 (simulating the effect of interference caused by phase difference between the three propagating beams, detector noise, and changes in the refractive index of the atmosphere). The detector noise and atmospheric variations effects were lumped together in a single white, zero-mean Gaussian noise term with a standard deviation of $10^{-3}$. The interference effect was simulated by considering that the propagating beams arrive with random phase differences at the detector, due to small movements of the receiver within the sampling period. Therefore, for each sampling period, an RMS value of the overall field intensity was calculated by co-averaging 10,000 intensity measurements.

As can be seen in Fig. 6, the noise is propagated through the identification process, thus affecting the model predictions. This problem can be alleviated by increasing the size of the identification window, which has a co-averaging effect on the propagation of noise, as illustrated in Fig. 7 where a 40-point window was used. However, the use of a larger window also increases the delay for the model predictions to settle after a discontinuity.

In the preceding simulations, an a priori knowledge of the system order was used in the modelling process. However, the order can also be estimated from the singular values calculated during the subspace identification procedure. Fig. 8a presents the singular value plot obtained in the course of the identification for the noise-free case and a 40-point window. The black bar indicates the order suggested by the algorithm as a compromise between the complexity and fitting accuracy of the model. As can be seen, the order suggested by the subspace implementation of Matlab matches the true order of the receiver motion dynamics.

After the introduction of interference, detector noise and atmospheric variations, the singular value plot is altered, as shown in Fig. 8b. In this case, subtle features in the trajectory are masked by the noise, so that the 2nd and 3rd singular values become much smaller than the first one. As a result, it becomes apparent that a 1st order model, which captures the main trend of the motion, should be employed. In fact, the identification mismatch caused by not using the true order of the system is smaller than the noise contribution, because simpler models are less sensitive to noise. This is depicted in Fig. 9, in which the predictions were carried out by imposing the use of a 1st order model.
5 Conclusion

This paper presented a black-box identification framework for modelling the long-term fading of a THz communication link. It was shown that the resulting model can be used as a prediction tool, which could be of value for the real-time reconfiguration of mesh network topologies.

It can be argued that the most interesting aspect of the adopted state-space formulation is the flexibility with which the model could be augmented to include further measurement channels. For instance, assuming hexagonal cells providing ideal coverage between base stations, signals from a maximum of three emitters can reach the receiver at any instance. Provided that the origin of each signal could be identified (as part of a communications protocol), a multiple output Wiener model could be utilized, with the extra information from each output providing a tripling on the number of points in the estimation of the state space model. The algorithms could, therefore, be used as a prediction tool for large scale fading in a Point-to-Multi-Point (PMP) network, (which could be simply implemented using integrated antennas in automobile roof-tops). In the general case, if there are \( S \) measurement channels, the Wiener model can be written as

\[
\begin{align*}
\mathbf{x}[k+1] &= \mathbf{A}\mathbf{x}[k], \quad \mathbf{x}[k_0] = \mathbf{x}_0 \\
\mathbf{y}[k] &= \mathbf{C}\mathbf{x}[k], \\
\mathbf{E}_{\text{rx}}[k] &= \mathbf{G}\mathbf{y}[k]
\end{align*}
\]

where \( \mathbf{y} = [y_1, y_2, ..., y_3]^T \) and \( \mathbf{E}_{\text{rx}} = [E_1, E_2, ..., E_3]^T \) are column vectors of outputs for the linear dynamic and nonlinear static terms of the system and \( \mathbf{G} : \mathbb{R}^3 \rightarrow \mathbb{R}^3 \), \( \mathbf{E}_{\text{rx}} = \mathbf{G}(\mathbf{y}) \), is a multivariate nonlinear mapping.

It is worth noting that, if two sources were used in section 4, it would be possible to use a two-input nonlinear function \( \mathbf{G} \). Such a model structure would be in better agreement with the geometric relations in Equations (1)-(3), which depend on two variables \( \theta \) and \( L \). Moreover, it would allow the resolution of ambiguities such as the one depicted in Fig. 10a. In this figure, as the receiver Rx moves from right to left, there are different points in the trajectory for which the field intensity is the same (points 1 and 2, for example). A solution for such a problem consists of reducing the size of the moving identification window, so that the ambiguity would not be present in the time frame employed. Alternatively, if two transmitters \( \text{Tx}1 \) and \( \text{Tx}2 \) were used (Fig. 10b), the ambiguity would cease to exist.

Finally, it is worth noting that the Wiener system model structure can easily take into account Doppler phenomena, which would provide an extra output measurement in addition to the field intensity, therefore improving the state estimates. In this case, the Doppler-shifted output would be related to the state variables describing the speed of the receiver.

For the same receiver motion pattern, the use of more output channels leads to a better estimate of the dynamics and initial state of the motion. Conversely, it can be stated that a larger noise level may be tolerated for a given estimation accuracy. In this case, the subspace identification algorithm can be seen as a data fusion process, in which information from different sources are used to reduce the uncertainty in the identification of the dynamic part of the Wiener system.

Apart from using the algorithm as part of a PMP network planning tool, there are other possible applications. For example, provided there is further integration of existing mobile technologies, there can be synergy with data acquired from medium-grade fibre-optic gyroscopes to provide position information. This could lead to alternative non GPS-based platforms for the deployment of location-based services obviating the need for excessive network bandwidth requirements. Applications of such location-based services include turn-by-turn navigation, guidance of emergency services to accident locations, mobile resource and logistics management, property tracking devices and fleet management systems. This would also provide the opportunity for communications providers to monitor flow rates on multiple lane highways automatically, at no additional expense. The statistical information could be supplied directly to planning authorities that need to consider traffic conditions over large stretches of road at complex junctions.

Finally, the proposed algorithm is of interest to developers providing U.S. E-911 compliant solutions (requirement for hand-held communications devices such as mobile phones and computing peripherals to be locatable within a 100m radius). In this sense, further developments to the work described could...
also be placed within the remit of anti-terrorist acts, although controversial applications (such as smart bombs) could also emerge as a by-product.

The present work could be extended as a back-up solution for the civil aviation industry when ground-based radars are not operational. In this context, it would complement the recent developments in GPS-based altimeter systems (such as the CELLDAR system, developed by Siemens), which uses the reflection of digital telephone signals from the sides of aircraft or boats to detect and track their movement. Subspace algorithms could be used when GPS systems are not operational due to natural disasters such as solar flares.

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