A Deconvolution Method to Remove Distortion Caused by Antenna Radiation Pattern from Measurement

Huajian Cui*(1), Rafael Caldeirinha(1), and Juergen Richter(2)

(1) Instituto de Telecomunicações, Polytechnic Institute of Leiria, Campus 2, 2411-901 Leiria, Portugal}
Email: huajian.cui@co.it.pt, rcaldeirinha@estg.ipleiria.pt

(2) Radiowave propagation and System design Research Unit, University of Glamorgan, CF37 1DL, UK.
Email: jrichter@glam.ac.uk

ABSTRACT: The influence of vegetation on radiowave signals has become an important aspect of the design of wireless communication links. In recent years the theory of Radiative Energy Transfer has been adopted as a reliable tool to predict the radiowave propagation through and near vegetation. However one major factor influencing accuracy of the measurement is the radiation pattern of the receiver antenna. The measured pattern will be the convolution product of the antenna radiation pattern and the phase function of the vegetation medium. The measured pattern therefore needs to undergo a deconvolution process before enable to provide reliable information. This paper presents a deconvolution method developed using optimum compensation filtering to remove the distortion caused by the receiver antenna radiation pattern. A pre-filtering technique using auto/cross-correlation is utilised to improve the deconvolution results, as well as an error function is deployed to determine the optimal parameter in the iterative filter.

INTRODUCTION TO RET THEORY AND ILL-POSEDNESS

The theory of Radiative Energy Transfer (RET) provides a full wave solution for vegetation modelling and has successfully been adopted for modelling of propagation in the presence of vegetation at microwave and millimeter wave frequency [1, 2]. To accurately model radiowave propagation with vegetation present, the RET requires a set of 4 input parameters. These depend on factors such as frequency, type of vegetation, state of foliation etc. and need to be determined experimentally. However the measurement result is highly depended on the receiver antenna radiation pattern. The measured signal pattern is the convolution product of the phase function and the receiver antenna radiation pattern [3]. A deconvolution application has therefore to be applied to remove the influence of the receiver antenna radiation pattern. Deconvolution is not a linear and not always a straightforward operation.

The RET theory simulates the vegetation medium as a homogeneous environment consisting of randomly distributed scatterers ds. This model can be represented by a set of 4 parameters: σ_a the absorption coefficient, σ_s the scattering coefficient, α the ratio between the forward lobe and the total scattered power, and β the beamwidth of the forward lobe [1, 2]. In the transport theory, it is assumed that the various scattered wave trains are uncorrelated in phase [1]. Hence the power can be added in real quantities at the receiver side. The radiation pattern of a typical antenna, however, is not an ideal pulse but a curve comprised of a mainlobe and a significant amount of sidelobes. While placing the receiver antenna inside the vegetation, both its mainlobe and sidelobes are receiving signals from rays both being directly transmitted from the transmitter and scattered from all the trees surrounding the receiving antenna [3]. This results in a convolution product of the phase function and the receiver antenna radiation pattern. Its expression is given by:

$$p_{RX}(\theta) = i(\theta) * g_{RX}(\theta) \tag{1}$$

where p_{RX} represents the measured power strength, g_{RX} denotes the radiation pattern of the receiver antenna, $i(\theta)$ denotes the phase function and θ is the rotation angle. Converted version of (1) in the transform domain is:

$$P_{RX}(\omega) = I(\omega) G_{RX}(\omega) \tag{2}$$

where P_{RX}, I and G_{RX} are the Fourier Transform of p_{RX}, i and g_{RX} respectively; ω is the variable in the transform domain corresponding to \theta in the original domain.

978-1-4244-4885-2/10/$25.00 ©2010 IEEE

Equation (2) suggests that a straightforward solution of the deconvolution can be achieved by inverse Fourier Transform of $I(\omega)$, which would be the result of division of $P_{RX}(\omega)$ over $G_{RX}(\omega)$, *i.e.* $I(\omega)=P_{RX}(\omega)/G_{RX}(\omega)$. However the presence of random noise in the signal and the resolution limits of the computer processing can generate large spike errors in the division. These errors can consequently swamp most of the useful information contained in $i(\theta)$ after inverse Fourier Transform. This is known as the ill-posed problem [4].

MEASUREMENT AND PRE-FILTERING TECHNIQUE

Measurements were conducted in a controlled indoor environment (anechoic chamber), which has an interior physical size of $5.60m\times2.25m\times2.40m$. The transmitter uses a $10\ dBi$ standard gain horn antenna. For the majority of the examples presented in this paper a $20\ dBi$ Gaussian horn antenna was used a receiver antenna, but measurements were also conducted with standard gain horns with gains ranging from 10 to $20\ dBi$.The distance between the transmitter and the receiver is sufficiently large to ensure the far-field conditions.

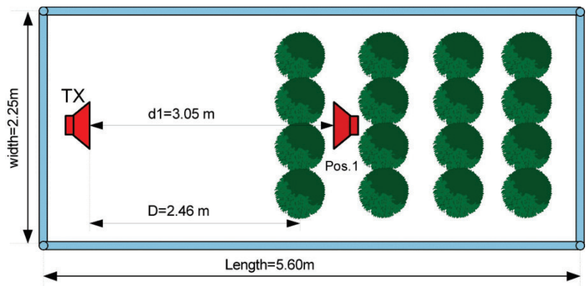

Fig. 1 Measurement geometry in the presence of vegetation.

The measurement was conducted using 16 Ficus trees to form a small scale vegetation body representing a miniature forest. The receiver antenna placed at position 1 has a 0.59m of vegetation depth as shown in Fig. 1 and rotated around its own vertical axis.

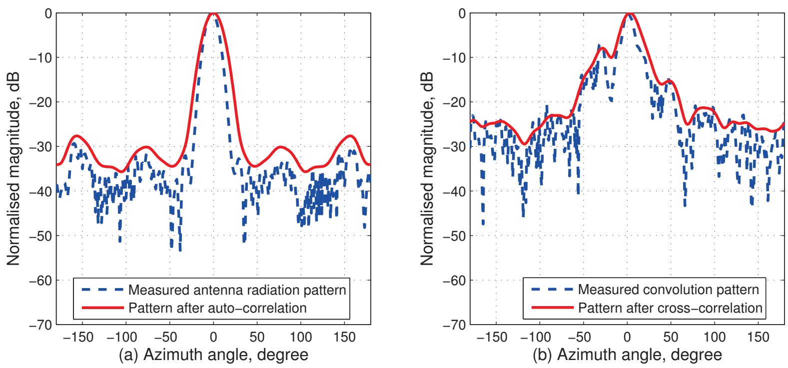

Fig. 2. Measured (a) Gaussian antenna radiation pattern and its autocorrelation and (b) reradiation pattern and its crosscorrelation.

The measured Gaussian horn radiation pattern was obtained in the absence of vegetation as shown in Fig. 2a. The measured received signal levels with rotation angle are shown in Fig. 2b. The maximum signal occurs when the antennas are boresight (azimuth angle $\theta=0$). Patterns after auto- and cross-correlation prefiltering are also demonstrated in Fig. 2a and Fig. 2b respectively. The new patterns have become much smoother curves, which is advantageous for the deconvolution operation. Auto- and cross-correlation prefiltering helps convergence and provides noise reduction and ensures convergence of the iterative transform domain methods while also increasing the rate of convergence [5]. Furthermore, random noise in the measurement data will be significantly reduced as demonstrated in Fig. 2. More details of prefiltering are documented in [3].

DECONVOLUTION BY OPTIMUM COMPENSATION FILTERING

Due to the ill-posed problem, accurate deconvolution cannot be undertaken by division in the transform domain. $P_{RX}(\omega)$ needs to undergo suitable filtering, $F(\omega)$, to produce the optimal estimate $I_e(\omega)$ of $I(\omega)$.

$$I_e(\omega) = P_{RX}(\omega)\cdot F(\omega) \tag{3}$$

The optimum compensation filtering deconvolution is documented by S. M. Riad et.al. in [6]. Two criteria, the Minimum Mean-Square-Error (MMSE) and the errors-control criterion, are deployed to iteratively determine the optimisation filter:

$$F(\omega) = G_{RX}^{*}(\omega) \Big/ \left|G_{RX}(\omega)\right|^2 + \lambda \tag{4}$$

where in (4) the superscript * denotes complex conjugate, λ is the optimisation parameter, which is iteratively determined based on a compromise between signal consistency and noise minimisation. The optimum compensation filter, $F(\omega)$, represents a form of the Wiener filter. Equations (3) and (4) show that, if $P_{RX}(\omega)$ and $G_{RX}(\omega)$ are known, the optimal filter $F(\omega)$ will be available by (4) once the optimal parameter λ is determined, and consequently $I_e(\omega)$ can be calculated by (3). Hence $P_{RX}(\omega)$ and $G_{RX}(\omega)$ need to be known to attain $I_e(\omega)$. In practice $g_{RX}(\theta)$ and $p_{RX}(\theta)$ are measured.

The value of parameter λ is approximately located in the range determined by the Bennia-Riad criteria documented in [6]. The error function is defined in the original domain by:

$$e(\theta) = p_{RX}(\theta) - i_e(\theta) * g_{RX}(\theta) \tag{5}$$

where $p_{RX}(\theta)$ represents the measurement pattern, $g_{RX}(\theta)$ represents the measured Gaussian horn radiation pattern and $i_e(\theta)$ represents the deconvolution pattern, *i.e.* the best restoration of $i(\theta)$. The error function must be carefully interpreted. Two parameters are used for its evaluation: the mean value $\bar{e} = \frac{1}{N}\sum_{k=1}^{N} e(\theta)$ and the standard deviation $\xi = \left\{\frac{1}{N}\sum_{k=1}^{N}\left[e(k)-\bar{e}\right]^2\right\}^{1/2}$, where N denotes the number of measurement samples. Ideally $\bar{e}$ should be zero, therefore the absolute value of $\bar{e}$ needs to be minimised.

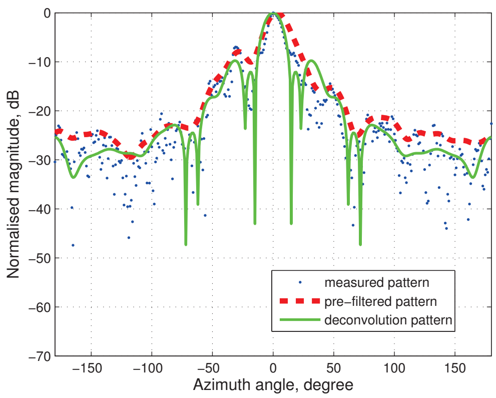

Fig. 3. Demonstration of the optimum compensation deconvolution result, $\lambda = 12.67\ dB$.

Minimum of the standard deviation occurs at $\lambda_1 = -6.26\ dB$ and the absolute minimum of mean value occurs at $\lambda_2 = 12.67\ dB$. Error functions are calculated according to (5) and find that choosing $\lambda_2 = 12.67\ dB$ provides smaller values in the error function and less fluctuation than $\lambda_1 = -6.26\ dB$, so the restored function pattern, after convolution with the prefiltered Gaussian horn radiation pattern, resembles the measurement pattern more closely. Therefore $12.67\ dB$ presents the better choice for parameter λ. The restored pattern after deconvolution is shown in Fig. 3. For comparison, the measured pattern and the pre-filtered pattern are overlaid. It is evident that the deconvolution pattern preserves useful information, or fluctuation, as well as significantly eliminates random noise.

IMPROVEMENTS TO RET INPUT PARAMETER EXTRACTION USING DECONVOLUTION

This section quantifies the improvements made to the extraction of RET input parameters from measurement data using Deconvolution. All 4 input parameters α, β, $k_e = \sigma_a + \sigma_s$ and $W = \sigma_s / (\sigma_a + \sigma_s)$ [1, 2] have been extracted from measurements at position 1 as described in [3] with and without the use of Deconvolution. Tab. 1 for example shows the extracted RET input parameter values from measurements using a $20\ dBi$ Gaussian horn antenna at 20 GHz for both cases.

Table 1 Extracted RET input parameters from measurement with 20 dBi Gaussian horn at 20 GHz.

	α	β	$k_e (dB/m)$	W
With Deconv.	0.96	22.5^o	6.78	0.49
Without Deconv.	0.96	21^o	6.78	0.46

Table 2 Calculated rms errors at measurement position 1.

Horn antenna	With Deconv.	Without Deconv.
$20\ dBi$ Gaussian horn	$5.84\ dB$	$6.2\ dB$
$20\ dBi$ standard gain horn	$8.74\ dB$	$13.36\ dB$
$15\ dBi$ standard gain horn	$9.53\ dB$	$12.26\ dB$
$10\ dBi$ standard gain horn	$8.38\ dB$	$17.72\ dB$

Input parameters have been extracted for all available measurement antennas again with and without the use of Deconvolution. They have consequently been applied to generate simulated directional spectra using the RET. These directional spectra are then compared with the measured directional spectra. The RMS errors between measured and simulated curves are listed in Tab. 2. As can be seen the RMS errors is significantly reduced, when deconvolution is deployed. It is also obvious that the improvement due to deconvolution is greater for wider and non-Gaussian antenna radiation patterns. This is as expected since the application of the RET to radiowave propagation through vegetation in [1] assumes narrow beamwidth Gaussian shape radiation patterns the greater deviation from this, the greater the distortion by the actual antenna pattern, now compensated by the used of deconvolution.

CONCLUSION

This paper demonstrates an improved technique to extract the input parameters of the RET theory from measurement data. The paper explains how the antenna radiation pattern affects the measured result and why straightforward division deconvolution cannot work. The iterative optimum compensation filtering is introduced and applied to measured patterns, as well as a prefiltering technique. Then an error function criterion is deployed to determine the best choice of parameter λ. Finally improvements from restored phase function patterns are demonstrated by calculated RMS results. This paper shows a successful extension of the application of the optimum compensation filtering technique to a measured RET phase function pattern distorted by the receiver antenna radiation pattern.

REFERENCES

[1] R. A. Johnson, and F. Schwering, “A transport theory of millimeter wave propagation in woods and forests” New Jersey, Feb. 1985.

[2] N. C. Rogers, A. Seville, J. Richter, D. Ndzi, N. Savage, R. Caldeirinha, A. K Shukla, M. O. Al-Nuaimi, E. Vilar and J. Austin, “A generic model of 1-60 GHz radio propagation through vegetation-final report”, Tech. Rep., Radiocommunications Agency, May 2002.

[3] H. Cui, “Extraction of input parameters for the theory of radiative energy transfer using deconvolution”, Ph.D. thesis, University of Glamorgan, U.K., Mar. 2009.

[4] S. M. Riad, “The deconvolution problem: an overview,” Proc. IEEE, vol.74, no. 1, pp. 82-85, Jan. 1986.

[5] P. B. Crilly, A. Bernardi, P. A. Jansson and L. Silva, “Improving the convergence rate of Jansson's deconvolution method” IEEE Trans. Instrum. Meas., vol.51, pp. 1142-1144, Dec. 2002.

[6] S. M. Riad and R. B. Stafford, “Impulse response evaluation using frequency domain optimal compensation deconvolution,” in Proc. 23rd Midwest Symp. on Circuits and Systems (Toledo, OH), pp. 521-525, Aug. 1980.