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Key Points:

- An MLS-based algorithm to resolve two adjacent rays reflected from the front and the back surfaces of a board-shaped material is proposed
- The performance of the proposed algorithm is evaluated through comparison with the CRLB
- Typical board-shaped building materials are measured for various incident angles to validate the algorithm

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Two-Ray Reflection Resolution Algorithm for Planar Material Electromagnetic Property Measurement at the Millimeter-Wave Bands

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Abstract Electromagnetic (EM) reflection properties of building materials and structures have been investigated through practical measurements. However, the finite thickness of measured materials makes it challenging to resolve the rays reflected from the front and the back surfaces. In this paper, we therefore present a three-step minimum least squares-based algorithm to resolve two closely adjacent rays reflected from the front and the back surfaces of a board-shaped material. Our analytical and numerical results show that the proposed algorithm achieves the Cramér-Rao lower bound. The proposed algorithm is validated using measurement data for various materials and incident angles in the 40–50 GHz frequency band. The validation results show that the proposed algorithm is capable of resolving two closely adjacent rays with a root-mean-square deviation that is smaller than 0.08. Main applications of the proposed algorithm can be found in the frequency domain measurements of the EM wave reflections by typical building structures, e.g., window glass, doors, ceiling, and floors.

1. Introduction

Over 80% of mobile traffic takes place indoors, and it is predicted that mobile traffic will increase by up to 1,000 times in the next decade (Cisco, Accessed Accessed 2019). Therefore, modeling indoor radio propagation and wireless channel is fundamental for the design and evaluation of wireless networks (De la Roche et al., 2012). Moreover, the envisaged application of millimeter wave (mmWave) communications in future 5G/B5G networks put forward requirements on broad bandwidth indoor channel modeling (Rappaport et al., 2013; Samimi & Rappaport, 2016). Accurate mmWave indoor channel simulations are critical for the design, evaluation, and deployment of future mmWave networks. The ray tracing (RT) and ray launching (RL) algorithms are commonly employed to predict the indoor radio channels (Casino et al., 2016; Chen et al., 2017; Dai et al., 2017). To support the RT/RL-based indoor wireless channel simulation, the attenuation, diffraction, scattering, and reflection of electromagnetic (EM) waves by typical planar building materials have to be investigated based on measurement (Azar et al., 2014; Burnside & Burgener, 1983; Zhekov et al., 2018). Due to the finite thickness of the materials used in buildings, the measured reflection is typically comprised of multiple reflection rays (Piesiewicz et al., 2008). In RT/RL algorithms, the contribution of the first ray to the reflection is usually modeled applying the Fresnel coefficients, for the sake of simplicity (Sheikh et al., 2016; Yun & Iskander, 2015). However, neglecting the high-order rays leads to inaccurate channel simulation. Fortunately, due to attenuation loss inside the material at mmWave, the high-order reflections can be neglected in comparison with the first and the second rays (see Figure 1). Therefore, an alternative way to simulate reflections by board-shaped building materials is to simulate the two main closely adjacent rays, whose behavior needs to be characterized through measurement. In order to analyze the impact of various types of building materials on EM waves, frequency domain measurements are usually performed using a vector network analyzer (VNA) (Azar et al., 2014; Hajisaeid et al., 2018; Zhekov et al., 2018). To characterize the two rays reflected by planar building materials, the two rays have to be resolved from measurement data.

Figure 1. Multiple reflections of the measured board-shaped materials. θ_i denotes the incident angle.

Moreover, EM properties of planar building materials have been characterized through VNA-based measurements (Degli-Esposti et al., 2017; Hajisaeid et al., 2018; Martin et al., 2017; Sagnard et al., 2005b, 2005a). Nevertheless, accurate measurements of EM properties, e.g., the complex permittivity, of building materials are challenging in an open space environment (Ahmadi-Shokouh et al., 2009, 2011). In some state-of-the-art literature, multiple reflections inside the planar material have been considered in homogeneous material characterization. In (Singh et al., 2017), a three-ray reflection model is designed to characterize building materials assuming that the material under measurement has a fixed complex permittivity. In (Tian et al., 2019), infinite reflections inside the planar material have been taken into account. In general, the accuracy of computation depends on the considered number of internal reflections and the position of the receiver. The impact of the number of internal reflections on the accuracy of a lossless board-shaped material is investigated in (Plouhinec & Uguen, 2011). When the high-order reflections can be neglected, a resolution of the first and the second rays facilitates simpler estimation algorithm for estimation of material's EM properties.

In this paper, we focus on the characterization of the spatial resolution of the two-ray reflection model from planar building materials in the VNA-based measurement. The proposed algorithms and analysis are validated on actual material samples. However, resolving closely adjacent arriving multipath components from measurement data is still challenging via inverse fast Fourier transform (IFFT) methodologies (Tewari et al., 2014; Yang et al., 2001; Zheng et al., 2015) due to their insufficient time domain resolution. In this paper, we propose a three-step minimum least squares (MLS)-based algorithm to resolve two adjacent rays reflected from the front and the back surfaces of a board-shaped material. To overcome the problem of multiple local minima in conventional MLS-based algorithms, the method of moments (MoM) (Kay, 1993) without optimality property is employed to obtain a rough estimate as the initial point of the iteration. The performance of the proposed algorithm is evaluated through comparison with the Cramér-Rao lower bound (CRLB). A closed-form expression of the CRLB is derived as a benchmark of performance. Moreover, typical building materials, including a wooden board, a plaster board, and a granite board, are measured for various incident angles to validate the algorithm. Comparisons between the CRLB and measurements show that the proposed algorithm is capable of resolving two closely adjacent rays with an excellent accuracy.

It is worth noting that the proposed model is limited to cases where powers of the main reflection and the first-order internal reflection are much greater than that of the combination of high-order reflections, multipath components in the measurement environment, and measurement noise.

The rest of this paper is organized as follows. Section 2 introduces the system model and states the problem. In Section 3, the MLS-inspired algorithm is proposed. In Section 4, the CRLB is analytically derived in a closed-form expression as a benchmark of performance. In Section 5, numerical results on the performance of the algorithm are provided. In Section 6, the algorithm is practically validated through measurements. Finally, Section 7 concludes this paper.

2. Signal Model and Problem Statement

In order to properly characterize the signal contributions from indoor building structures, e.g., board-shaped materials, we need to consider reflections and transmissions within the material as shown in Figure 1. As can be seen, the reflected EM waves are comprised by the direct reflection ray (named the first ray in the remainder of this paper) and the reflection ray from the back side of the board (denoted as the second

Figure 2. Comparison of the two-ray model with the infinite-reflections model, where $\gamma_1 = 1.14$ and $\gamma_2 = 0.44$.

ray). The measured S_{21} consists then of both these rays as well as high-order reflections inside the material, other multipath components in the measurement environment, and measurement noise. In the mm-Wave band, since the attenuation of the EM waves in the material is high, we assume that only the first and the second rays are dominant, and high-order reflections inside the material, other multipath components in the measurement environment, and measurement noise are much weaker than the first and the second rays. Therefore, the measured S_{21} is approximate to

$$S_{21}[n] \approx \Gamma_1[n] \exp(j\omega[n]r_1/c) + \Gamma_2[n] \exp[j(\omega[n]r_2/c + \phi)], \quad (1)$$

where r_1 and $r_2 = r_1 + 2\Delta d \text{Re}(\sqrt{\epsilon_r - \sin^2 \theta_i})$ are the equivalent path lengths of the first and the second rays considering adjustment of the speed of light in the material, $\Gamma_1[n] \exp(j\omega[n]r_1/c)$ is the S_{21} parameter of the first ray, and $\Gamma_2[n] \exp[j(\omega[n]r_2/c + \phi)]$ is the S_{21} parameter of the second ray; $n = 1, 2, \dots, N_\omega$ is the index of frequency samples; ϕ is the phase shift relative to the first ray; $c = 3 \times 10^8$ m/s is the speed of light. $\Gamma_1[n]$ and $\Gamma_2[n]$ are the real amplitudes of the first and the second rays at the surface of the material, respectively, whereas $\Delta r = r_2 - r_1$ is the equivalent path difference between the second and the first rays. According to the Friis transmission formula, the amplitudes $\Gamma_1[n]$ and $\Gamma_2[n]$ can be modeled to be inversely proportional to $\omega[n]$. Hence, we assume that $\Gamma_1[n] = \gamma_1/\omega[n] \times 10^9$, $\Gamma_2[n] = \gamma_2/\omega[n] \times 10^9$, where

$$\gamma_1 = \frac{0.3\sqrt{G_t G_r} |\Gamma|}{2r_1} \quad (2)$$

and

$$\gamma_2 = \frac{0.3\sqrt{G_t G_r} |\Gamma| |T|^2 \exp(-4\alpha L)}{2r_2} \quad (3)$$

are two scaling factors, where Γ and T denote the reflection coefficient and the transmission coefficient of the surface, respectively. α denotes the attenuation constant. G_t and G_r denote gains of the transmit and the receive measurement antennas, respectively. L denotes the effective thickness of the material under measurement (Singh et al., 2017, Eq. (1)).

Figure 3. Error upper bound computed by (6).

To validate that the first and the second rays are dominant, a comparison of the two-ray model with the infinite-reflection model (Tian et al., 2019) is illustrated in Figure 2, where $\Gamma = -0.2$, $T = 1 + \Gamma = 0.8$, $\exp(-4\alpha L) = 0.6$, $G_t = G_r = 15.8$ dBi, $S_{21, \text{two-ray}}(\omega)$ is generated by (1), and

$$S_{21, \text{infinite-reflection}}(\omega) = \Gamma_1 \exp(j\omega r_1/c) + \sum_{n_r=2}^{\infty} \Gamma_{n_r} \exp[j(\omega r_{n_r}/c + n_r \phi)], \quad (4)$$

where $\Gamma_{n_r} = \gamma_{n_r}/\omega \times 10^9$ and $\gamma_{n_r} = \frac{0.3\sqrt{G_t G_r} |\Gamma|^{2n_r-1} |T|^2 \exp(-4\alpha L(n_r-1))}{2r_{n_r}}$.

It is observed that the contribution of the second ray is not negligible and will be analyzed in this paper.

Furthermore, we use the infinity norm distance between S_{21} parameters generated by the two-ray model and the infinite-reflection model to evaluate the error introduced by neglecting high-order reflections, i.e.,

$$e = \max_{\omega \in \mathbb{R}^+} \left\{ |20\log_{10}|S_{21, \text{infinite-reflection}}(\omega)| - 20\log_{10}|S_{21, \text{two-ray}}(\omega)|| \right\}. \quad (5)$$

To avoid the brutal-force search of ω that leads to maximum distance between two S_{21} parameters, the error is upper bounded as

$$\begin{aligned} e &= \max_{\omega \in \mathbb{R}^+} \left\{ \left| 10\log_{10} \left| \frac{\Gamma_1 \exp(j\omega r_1/c) + \sum_{n_r=2}^{\infty} \Gamma_{n_r} \exp[j(\omega r_{n_r}/c + n_r \phi)]}{\Gamma_1 \exp(j\omega r_1/c) + \Gamma_2 \exp[j(\omega r_2/c + \phi)]} \right| \right| \right\} \\ &\leq \max_{\omega \in \mathbb{R}^+} \left\{ \left| 10\log_{10} \left| 1 + \frac{\sum_{n_r=3}^{\infty} \Gamma_{n_r}}{\Gamma_1 - \Gamma_2} \right| \right| \right\} \\ &\triangleq e_U. \end{aligned} \quad (6)$$

The error upper bound e_U is illustrated in Figure 3. From Figure 3, we observe that the error upper bound is less than 0.3 dB at all frequency bands, and the contribution of high-order rays is slight in comparison with two dominant rays and thus is negligible.

Figure 4. An example of IFFT-based two ray resolution, where $\gamma_1 = 1$, $\gamma_2 = 0.4$, and $\phi_0 = \pi$.

Discerning the two closely adjacent rays is not straightforward in practice. Traditionally, properties of reflection rays are estimated through IFFT-based algorithms from frequency domain measurements (Zheng et al., 2015). However, the resolution capability of the measurement is constrained by the measurement bandwidth B in IFFT-based algorithms. When $\Delta r < \frac{c}{B}$, the two rays in (1) are not resolvable. Therefore, for a material whose thickness Δd is smaller than $c/(2 \cos(\theta_i) B \sqrt{\epsilon_r})$ with ϵ_r denoting the relative permittivity of the material, the two adjacent rays are not resolvable by IFFT. Even if the measurement bandwidth is as large as 10 GHz, the corresponding resolution of Δr is only 3 cm, which is comparable to the thickness of the measured material. It is difficult to distinguish them in the time domain, because of the side lobes introduced by the IFFT with rectangular window in the frequency domain (.). Example of channel impulse response computed by IFFT from simulated $S_{21}[n]$ without noise is shown in Figure 4 for various Δr , where $\gamma_1 = 1$, $\gamma_2 = 0.4$, and $\phi_0 = \pi$. We observe that since $\Delta r \leq 4$ cm, the two rays appear as a single ray after IFFT from $S_{21}[n]$, and they are not distinguishable through IFFT-based algorithms.

3. Reflection Rays Resolution

To overcome the above problem, an algorithm to separate the two rays is presented in the following.

First, the receive power in the two-ray model is computed

$$|S_{21}[n]|^2 = \Gamma_1[n]^2 + \Gamma_2[n]^2 + 2\Gamma_1[n]\Gamma_2[n] \cos(\omega[n]\Delta r/c + \phi). \quad (7)$$

Now, multiplying both sides of (7) by $\omega^2[n]$, we have

$$\begin{aligned} y[n] &= |S_{21}[n]|^2 \omega^2[n] \\ &= \gamma_1^2 + \gamma_2^2 + 2\gamma_1\gamma_2 \cos(\omega[n]\Delta r/c + \phi) + P_m[n], \end{aligned} \quad (8)$$

where $P_m[n]$ is the error introduced by the other multipath components and noise. Since the first and the second rays are dominant, it can be assumed that the combined effect of the other multipath components and noise behave like white noise, i.e., $P_m[n] \sim \mathcal{N}(0, \sigma_m^2)$ and $\sigma_m^2 \ll \gamma_i^2$, $i = 1, 2$.

In order to extract unknown parameters of both rays from the measured S_{21} , i.e., $[\hat{\gamma}_1, \hat{\gamma}_2, \Delta \hat{r}, \hat{\phi}]$, we propose an MLS method inspired algorithm. The basic mechanism of the MLS method is to minimize the mean square distance between the measured and the estimated S_{21} parameters, i.e.,

$$[\hat{\gamma}_1, \hat{\gamma}_2, \Delta \hat{r}, \hat{\phi}] = \arg \min \left\{ \frac{\sum_{n=1}^{N_f} |F(\hat{\gamma}_1, \hat{\gamma}_2, \Delta \hat{r}, \hat{\phi}, n) - y[n]|^2}{N_f} \right\}, \quad (9)$$

where

$$F(\hat{\gamma}_1, \hat{\gamma}_2, \Delta \hat{r}, \hat{\phi}, n) = \hat{\gamma}_1^2 + \hat{\gamma}_2^2 + 2\hat{\gamma}_1\hat{\gamma}_2 \cos(\omega[n]\Delta \hat{r}/c + \hat{\phi}). \quad (10)$$

It is worthwhile to note that (9) is a nonlinear least squares problem.

Figure 5. An example of $|F(\hat{\gamma}_1, \hat{\gamma}_2, \Delta\hat{r}, \hat{\phi}, n) - y[n]|^2$. At $\Delta r = 3$ cm, a slight error still exists due to the combination of high-order reflections inside the material, other multipath components in the measurement environment, and measurement noise, which are modeled as P_m in (5).

An example of the variation of $|F(\hat{\gamma}_1, \hat{\gamma}_2, \Delta\hat{r}, \hat{\phi}, n) - y[n]|^2$ as a function of $\Delta\hat{r}$ is plotted in Figure 5, where $\hat{\gamma}_1 = \gamma_1 = 1$, $\hat{\gamma}_2 = \gamma_2 = 0.1$, $\hat{\phi} = \phi = \pi$, $\Delta r = 0.03$ m, and $\sigma_m^2 = 10^{-2}$. It is observed from Figure 5 that the optimization can have numerous local minima. Therefore, given an inappropriate choice of initial points of iteration, an estimate of Δr may lead to a local minima of $|F(\hat{\gamma}_1, \hat{\gamma}_2, \Delta\hat{r}, \hat{\phi}, n) - y[n]|^2$ instead of the optimum estimate by implementing the conventional MLS method (Stoica et al., 1989). With a local best estimate of Δr , optimum estimates of other parameters could neither be obtained. However, performing an exhaustive search in (9) to jointly estimate $[\hat{\gamma}_1, \hat{\gamma}_2, \Delta\hat{r}, \hat{\phi}]$ is computational too expensive.

Thus, in order to reduce the computational complexity, we first estimate the $[\check{\gamma}_1, \check{\gamma}_2]$ and $[\Delta\check{r}, \check{\phi}]$, separately in the first two steps to obtain rough estimates. Then, we use the rough estimates $[\check{\gamma}_1, \check{\gamma}_2, \Delta\check{r}, \check{\phi}]$ as an input into the conventional MLS estimator to obtain $[\hat{\gamma}_1, \hat{\gamma}_2, \Delta\hat{r}, \hat{\phi}]$. The steps are explained in the following.

Step 1: We estimate $[\check{\gamma}_1, \check{\gamma}_2]$ using the MoM first. By defining

$$\begin{cases} \mu_0 = \frac{\sum_{n=1}^{N_f} y[n]}{N_f}, \\ \mu_k = \frac{\sum_{n=1}^{N_f-k} y[n]y[n+k]}{N_f-k}, k = 1, 2, \end{cases} \quad (11)$$

we obtain

$$\begin{cases} E[\mu_0] = \gamma_1^2 + \gamma_2^2, \\ E[\mu_k] = (\gamma_1^2 + \gamma_2^2)^2 + 2\gamma_1^2\gamma_2^2 \cos(k\Delta\omega\Delta r/c). \end{cases} \quad (12)$$

Following manipulations in Appendix A, we obtain the MoM estimators of $[\check{\gamma}_1, \check{\gamma}_2]$ from (12) as

$$\begin{cases} \check{\gamma}_1 = \sqrt{\frac{\mu_0 + \sqrt{\mu_0^2 - 4A}}{2}}, \\ \check{\gamma}_2 = \sqrt{\frac{\mu_0 - \sqrt{\mu_0^2 - 4A}}{2}}, \\ A = \frac{-\mu_2' + \sqrt{\mu_2'^2 + 8\mu_1'^2}}{4}, \\ \mu_k' = \mu_k - \mu_0^2. \end{cases} \quad (13)$$

Step 2: We estimate the $[\Delta\check{r}, \check{\phi}]$ using the estimated $[\check{\gamma}_1, \check{\gamma}_2]$. Hence, substituting $[\check{\gamma}_1, \check{\gamma}_2]$ from (13) into (9), we obtain

$$\begin{cases} [\Delta\check{r}, \check{\phi}] = \arg \min \left\{ \frac{\sum_{n=1}^{N_f} |z[n] - \cos(\omega[n]\Delta\check{r}/c + \check{\phi})|^2}{N_f} \right\}, \\ z[n] = \frac{y[n] - \check{\gamma}_1^2 - \check{\gamma}_2^2}{2\check{\gamma}_1\check{\gamma}_2}. \end{cases} \quad (14)$$

Figure 6. Examples of resolution, where $\gamma_1 = 1$, $\gamma_2 = 0.4$, and $\phi_0 = \pi$. The measurements are generated by (5).

The estimates of $[\Delta \hat{r}, \hat{\phi}]$ are then obtained from measurement data by exhaustive search.

Step 3: Using the output of steps 1 and 2 as an initial point, we obtain the final estimation $[\hat{\gamma}_1, \hat{\gamma}_2, \Delta \hat{r}, \hat{\phi}]$ using the well-known conventional nonlinear least square method. In this paper, we use the *lsqcurvefit* function in MATLAB 2018a software from Mathworks (Mathworks, 2019).

As an example, the amplitudes of $S_{21}[n]$ before and after applying the proposed estimation algorithm are shown in Figure 6, where $\gamma_1 = 1$, $\gamma_2 = 0.4$, and $\phi_0 = \pi$. From Figure 6, we observe that even though the Δr is as small as 2 cm, the algorithm is capable of resolving the two closely adjacent rays with excellent accuracy.

4. Cramér-Rao Lower Bound

From (8), the joint probability density function of $y[n]$ is represented as (15) given $[\gamma_1, \gamma_2, \Delta r, \phi, \sigma_m]$.

$$P(y[1], \dots, y[N_f]; \gamma_1, \gamma_2, \Delta r, \phi) = \frac{\exp \left[-\frac{\sum_{n=1}^{N_f} (\gamma_1^2 + \gamma_2^2 + 2\gamma_1\gamma_2 \cos(\omega[n]\Delta r/c + \phi) - y[n])^2}{2\sigma_m^2} \right]}{(2\pi\sigma_m^2)^{\frac{N_f}{2}}}. \quad (15)$$

The Fisher information matrix of the estimator, $\mathbf{I}(\gamma_1, \gamma_2, \Delta r, \phi)$, then is computed by

$$\mathbf{I}(\gamma_1, \gamma_2, \Delta r, \phi) = \frac{1}{\sigma_m^2} \sum_{n=1}^{N_f} \begin{bmatrix} I_{\gamma_1}^2[n] & I_{\gamma_1}[n]I_{\gamma_2}[n] & I_{\gamma_1}[n]I_{\Delta r}[n] & I_{\gamma_1}[n]I_{\phi}[n] \\ I_{\gamma_2}[n]I_{\gamma_1}[n] & I_{\gamma_2}^2[n] & I_{\gamma_2}[n]I_{\Delta r}[n] & I_{\gamma_2}[n]I_{\phi}[n] \\ I_{\Delta r}[n]I_{\gamma_1}[n] & I_{\Delta r}[n]I_{\gamma_2}[n] & I_{\Delta r}^2[n] & I_{\Delta r}[n]I_{\phi}[n] \\ I_{\phi}[n]I_{\gamma_1}[n] & I_{\phi}[n]I_{\gamma_2}[n] & I_{\phi}[n]I_{\Delta r}[n] & I_{\phi}^2[n] \end{bmatrix}, \quad (16)$$

where

$$\begin{cases} I_{\gamma_1}[n] = 2\gamma_1 + 2\gamma_2 \cos(\omega[n]\Delta r/c + \phi), \\ I_{\gamma_2}[n] = 2\gamma_2 + 2\gamma_1 \cos(\omega[n]\Delta r/c + \phi), \\ I_{\Delta r}[n] = -\frac{2\gamma_1\gamma_2\omega[n] \sin\left(\frac{\omega[n]\Delta r}{c} + \phi\right)}{c}, \\ I_{\phi}[n] = -2\gamma_1\gamma_2 \sin\left(\frac{\omega[n]\Delta r}{c} + \phi\right). \end{cases} \quad (17)$$

Therefore, from (16), the CRLB of estimating $[\gamma_1, \gamma_2, \Delta r, \phi]$ is given in a closed-form expression by

$$\begin{cases} \text{CRLB} \quad (\hat{\gamma}_1) = [\mathbf{I}^{-1}(\gamma_1, \gamma_2, \Delta r, \phi)]_{11} = \frac{G_{\hat{\gamma}_1}}{\sigma_m^2 G}, \\ \text{CRLB} \quad (\hat{\gamma}_2) = [\mathbf{I}^{-1}(\gamma_1, \gamma_2, \Delta r, \phi)]_{22} = \frac{G_{\hat{\gamma}_2}}{\sigma_m^2 G}, \\ \text{CRLB} \quad (\Delta \hat{r}) = [\mathbf{I}^{-1}(\gamma_1, \gamma_2, \Delta r, \phi)]_{33} = \frac{G_{\Delta \hat{r}}}{\sigma_m^2 G}, \\ \text{CRLB} \quad (\hat{\phi}) = [\mathbf{I}^{-1}(\gamma_1, \gamma_2, \Delta r, \phi)]_{44} = \frac{G_{\hat{\phi}}}{\sigma_m^2 G}, \end{cases} \quad (18)$$

where $G_{\hat{\gamma}_1}$, $G_{\hat{\gamma}_2}$, $G_{\Delta \hat{r}}$, $G_{\hat{\phi}}$, and G are computed by

$$\begin{cases} G_{\hat{\gamma}_1} = \det \left\{ \sum_{n=1}^{N_f} \begin{bmatrix} I_{\gamma_2}^2[n] & I_{\gamma_2}[n]I_{\Delta r}[n] & I_{\gamma_2}[n]I_{\phi}[n] \\ I_{\Delta r}[n]I_{\gamma_2}[n] & I_{\Delta r}^2[n] & I_{\Delta r}[n]I_{\phi}[n] \\ I_{\phi}[n]I_{\gamma_2}[n] & I_{\phi}[n]I_{\Delta r}[n] & I_{\phi}^2[n] \end{bmatrix} \right\}, \\ G_{\hat{\gamma}_2} = \det \left\{ \sum_{n=1}^{N_f} \begin{bmatrix} I_{\gamma_1}^2[n] & I_{\gamma_1}[n]I_{\Delta r}[n] & I_{\gamma_1}[n]I_{\phi}[n] \\ I_{\Delta r}[n]I_{\gamma_1}[n] & I_{\Delta r}^2[n] & I_{\Delta r}[n]I_{\phi}[n] \\ I_{\phi}[n]I_{\gamma_1}[n] & I_{\phi}[n]I_{\Delta r}[n] & I_{\phi}^2[n] \end{bmatrix} \right\}, \\ G_{\Delta \hat{r}} = \det \left\{ \sum_{n=1}^{N_f} \begin{bmatrix} I_{\gamma_1}^2[n] & I_{\gamma_1}[n]I_{\gamma_2}[n] & I_{\gamma_1}[n]I_{\phi}[n] \\ I_{\gamma_2}[n]I_{\gamma_1}[n] & I_{\gamma_2}^2[n] & I_{\gamma_2}[n]I_{\phi}[n] \\ I_{\phi}[n]I_{\gamma_1}[n] & I_{\phi}[n]I_{\gamma_2}[n] & I_{\phi}^2[n] \end{bmatrix} \right\}, \\ G_{\hat{\phi}} = \det \left\{ \sum_{n=1}^{N_f} \begin{bmatrix} I_{\gamma_1}^2[n] & I_{\gamma_1}[n]I_{\gamma_2}[n] & I_{\gamma_1}[n]I_{\Delta r}[n] \\ I_{\gamma_2}[n]I_{\gamma_1}[n] & I_{\gamma_2}^2[n] & I_{\gamma_2}[n]I_{\Delta r}[n] \\ I_{\Delta r}[n]I_{\gamma_1}[n] & I_{\Delta r}[n]I_{\gamma_2}[n] & I_{\Delta r}^2[n] \end{bmatrix} \right\}, \\ G = \det \left\{ \sum_{n=1}^{N_f} \begin{bmatrix} I_{\gamma_1}^2[n] & I_{\gamma_1}[n]I_{\gamma_2}[n] & I_{\gamma_1}[n]I_{\Delta r}[n] & I_{\gamma_1}[n]I_{\phi}[n] \\ I_{\gamma_2}[n]I_{\gamma_1}[n] & I_{\gamma_2}^2[n] & I_{\gamma_2}[n]I_{\Delta r}[n] & I_{\gamma_2}[n]I_{\phi}[n] \\ I_{\Delta r}[n]I_{\gamma_1}[n] & I_{\Delta r}[n]I_{\gamma_2}[n] & I_{\Delta r}^2[n] & I_{\Delta r}[n]I_{\phi}[n] \\ I_{\phi}[n]I_{\gamma_1}[n] & I_{\phi}[n]I_{\gamma_2}[n] & I_{\phi}[n]I_{\Delta r}[n] & I_{\phi}^2[n] \end{bmatrix} \right\}, \end{cases} \quad (19)$$

where $\det(\mathbf{X})$ denotes the determinant of the matrix $\mathbf{X}$ and $\mathbf{X}_{mn}$ denotes the element in the m th row and the n th column. In the numerical result section, the CRLB is employed as a performance benchmark of the three-step LMS algorithm presented here.

5. Numerical Results

Figure 6 validated that the algorithm is capable of resolving the two closely adjacent rays. Indeed, the mean square error (MSE) of the proposed algorithm is compared with the CRLB computed by (18) in Figure 7. For low the power of high-order reflections and other multipath components in the measurement environment, i.e., σ_m^2 , the proposed algorithm has an MSE that is close to the CRLB. Therefore, environments with less scatters are preferred to carry out the measurement.

From Figure 7, we also observe that the performance of the algorithm depends on ϕ . The impact of ϕ on the CRLBs is illustrated in Figure 8, where we observe that CRLBs are periodic functions of ϕ . For the measurement of a board-shaped material, when $\Delta r = 2\Delta d \text{Re}(\sqrt{\epsilon_r - \sin^2 \theta_i})$ changes, the value of $\omega[n]\Delta r/c$ changes rapidly at the mmWave band due to a large $\omega[n]$. From (17), we further observe that for a slight change of Δr , the change of $\omega[n]\Delta r/c$, with a relatively large value, is added onto ϕ , which has a limit range of $(0, 2\pi]$. Therefore, in the RL/RT-based channel simulation, ϕ can be assumed as a uniformly distributed

Figure 7. MSE of the estimators, where $\gamma_1 = 1$, $\gamma_2 = 0.4$, and $\Delta r = 3$ cm. Markers are simulation results from 3,000 realizations, and solid lines denote the CRLB computed by (18).

variable. To shed some light on the impact of the length difference Δr on the average MSE of the proposed estimators, we use the metric average CRLB (ACRLB) for each estimated parameter, which are defined as

$$\begin{cases} \text{ACRLB}(\hat{\gamma}_1) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \text{CRLB}(\hat{\gamma}_1) d\phi, \\ \text{ACRLB}(\hat{\gamma}_2) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \text{CRLB}(\hat{\gamma}_2) d\phi, \\ \text{ACRLB}(\Delta\hat{r}) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \text{CRLB}(\Delta\hat{r}) d\phi, \\ \text{ACRLB}(\hat{\phi}) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \text{CRLB}(\hat{\phi}) d\phi. \end{cases} \quad (20)$$

In Figure 9, the ACRLB versus Δr is plotted. Therein, only ACRLBs are given because the proposed algorithm is CRLB achieving, and simulating the algorithm for all possible ϕ is too computational expensive. From Figure 9, we observe that (1) the ACRLB decreases with an increasing Δr because the two rays are more easier to be distinguished with a large Δr , and (2) even though the Δr is large, the ACRLB can not be infinitely small due to the existence of multipath components but has a floor, which can be computed following some trivial derivations by letting $\Delta r \rightarrow +\infty$ as

$$\begin{cases} \text{CRLB}_f(\hat{\gamma}_1) = \frac{2\sigma_m^2\gamma_2^2 + \sigma_m^2\gamma_1^2}{K_1}, \\ \text{CRLB}_f(\hat{\gamma}_2) = \frac{2\sigma_m^2\gamma_1^2 + \sigma_m^2\gamma_2^2}{K_2}, \\ \text{CRLB}_f(\Delta\hat{r}) = \frac{N_f\sigma_m^2\gamma_1^2\gamma_2^2}{K_2}, \\ \text{CRLB}_f(\hat{\phi}) = \frac{\sigma_m^2\gamma_1^2\gamma_2^2 \sum_{n=1}^{N_f} \omega^2[n]}{c^2 K_2}, \end{cases} \quad (21)$$

Figure 8. The impact of ϕ on CRLBs of the estimators $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{\phi}$, and $\Delta\hat{r}$ where $\gamma_1 = 1$, $\gamma_2 = 0.4$, $\Delta r = 2$ cm, and $\sigma_m = 0.1$.

where

$$\begin{cases} K_1 = 4N_f (\gamma_1^4 + \gamma_2^4 - 2\gamma_1^2\gamma_2^2), \\ K_2 = \frac{2\gamma_1^4\gamma_2^4 N_f \sum_{n=1}^{N_f} \omega^2[n] - \left(\sum_{n=1}^{N_f} \omega[n] \right)^2}{c^2}. \end{cases} \quad (22)$$

6. Measurement Validation

In order to validate the algorithm, a measurement campaign was performed on various typical building structure materials, as shown in Figure 10. In the system, a VNA is employed to measure the $S_{21}[n]$ of the propagation channel via reflection from the analyzed materials, $n = 1, 2, \dots, N_f$. In this paper, the measurements are carried out at 40–50 GHz and with $N_f = 41$. Hence, $\omega[n] = 80\pi + (n-1)\Delta\omega$ Grad/s, and $\Delta\omega = 0.5\pi$ Grad/s. Two horn antennas with a same gain of 15.8 dBi and a 3 dB beam width of 0.25 rad are connected to the VNA via cables to transmit and receive TE polarized waves. The cable losses are 20 dB at 45 GHz. To remove the combined response of coaxial cable and connectors, the VNA is calibrated by standard 2-port SOLT calibration method. With high directivity, the horn antennas effectively reduce the interference from unwanted directions efficiently. A laptop is used to collect and analyze the data from the VNA.

The considered typical materials of building structures are a wooden board, a plaster board, and a granite board. The thickness of the measured materials is less than 2 cm. Considering 10λ distance as the boundary of the far field, it is then equal to 7.5 cm at 40 GHz and 6 cm at 50 GHz. Therefore, the distance between the antennas and the reflection position is 50 cm that satisfies the far-field condition of the considered frequency band. Our examples consider two incident angles, i.e., $\theta_i \in \{\frac{\pi}{6}, \frac{\pi}{3}\}$.

Figure 9. ACRLBs of the estimators $\hat{\gamma}_1$, $\hat{\gamma}_2$, $\hat{\phi}$, and $\Delta\hat{r}$ where $\gamma_1 = 1$ and $\sigma_m = 0.1$.

Using the measured data, results of two-ray resolution using the proposed algorithm are given in Table 1 and illustrated in Figure 11. From (8), the estimated $\hat{\sigma}_m$ is obtained by

$$\hat{\sigma}_m = \sqrt{\frac{1}{N_f} \sum_{n=1}^{N_f} \left[|S_{21}[n]|^2 \omega^2[n] - \hat{\gamma}_1^2 - \hat{\gamma}_2^2 \right]^2}. \quad (23)$$

It is observed that the estimated $\hat{\sigma}_m$ from measurements is less than 0.1 and combination of the separated rays matches the measured S_{21} parameter very well.

It is worth noting that more incident angles have to be considered in measurements using the proposed MLS-based algorithm in the future. To support the RL/RT algorithms, appropriate empirical characterization of the two-ray model is required to support RL/RT-based channel models.

Table 1
Measured parameters

Material	θ_i	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\Delta\hat{r}$ (cm)	$\hat{\phi}$ (rad)	$\hat{\sigma}_m$
Wooden board	$\pi/6$	0.49	0.20	2.50	-0.19	0.05
	$\pi/3$	0.45	0.19	3.34	-0.33	0.03
Plaster board	$\pi/6$	0.44	0.20	2.53	2.25	0.03
	$\pi/3$	0.28	0.13	2.67	4.76	0.02
Granite	$\pi/6$	0.71	0.23	6.34	-1.84	0.08
	$\pi/3$	0.54	0.24	7.06	1.42	0.04

Figure 10. Measurement set-up: measurement equipment, measurement scenario, antenna radiation pattern, and considered materials.

7. Conclusions

A three-step MLS-inspired algorithm to resolve two adjacent rays for board-shaped material EM property measurement is proposed with the assumption that powers of the main reflection and the first-order internal reflection are much greater than that of the combination of high-order reflections, multipath components in the measurement environment, and measurement noise. The performance of the proposed algorithm is shown to be close to the CRLB. The proposed algorithm is validated by measurements of typical board-shaped building materials, e.g., wooden board, plaster board, and granite, that are measured. The analysis shows that the algorithm is capable of resolving two closely adjacent rays with an excellent accuracy from measurement at the mmWave frequencies, e.g., 40–50 GHz. The proposed algorithm can be applied in the measurement-based board-shaped building material characterization. In the future, more building materials will be measured and characterized under various incident angles through measurements using the proposed algorithm. A database will be established accordingly. Based on the data base, empirical two-ray building material reflection models will be built and integrated in RT/RL-based channel models, which can be applied in the prediction, simulation, and analysis of EM wave propagation in indoor environments at the mmWave frequencies for 5G and other emerging wireless systems.

Appendix A: Proof of (13)

From (12), the MoM estimators for γ_1 , γ_2 , ϕ , and Δr are defined as the solution to the simultaneous equations

$$\begin{cases} \mu_0 = \gamma_1^2 + \gamma_2^2, \\ \mu_k = (\gamma_1^2 + \gamma_2^2)^2 + 2\gamma_1^2\gamma_2^2 \cos(k\Delta\omega\Delta r/c). \end{cases} \quad (\text{A1})$$

By defining $\mu'_k = \mu_k - \mu_0^2$, we have

$$\begin{cases} \mu'_1 = 2\gamma_1^2\gamma_2^2 \cos(\Delta\omega\Delta r/c), \\ \mu'_2 = 2\gamma_1^2\gamma_2^2 [2\cos^2(\Delta\omega\Delta r/c) - 1]. \end{cases} \quad (\text{A2})$$

Substituting μ'_1 into μ'_2 , we obtain

$$\mu'_2 = \frac{\mu_1'^2}{\gamma_1^2\gamma_2^2} - 2\gamma_1^2\gamma_2^2. \quad (\text{A3})$$

Figure 11. Results of two-ray resolution from measurements with two incident angles, i.e., $\theta_i \in \{\frac{\pi}{6}, \frac{\pi}{3}\}$. Typical building materials, i.e., a wooden board, a plaster board, and a granite board are measured.

Combining to solve Equation (A3) and $\mu_0 = \gamma_1^2 + \gamma_2^2$, we obtain (13).

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