High-speed FDTD calculation method specialized for automotive radar analysis

Tomokazu Okugi¹, a) and Kan Okubo²

¹ Technical Research Center, Mazda Motor Corporation, 2–5 Moriya-cho, Kanagawa-ku, Yokohama, Kanagawa 221–0022, Japan
² Faculty of System Design, Tokyo Metropolitan University, 6–6 Asahigaoka, Hino, Tokyo 191–0065, Japan

Abstract: The propagation analysis of an automotive radar using the finite-difference time-domain (FDTD) method uses tens of billions of analysis cells, and the simulation time is several days to several weeks. This study developed a method of accelerating the FDTD simulation for automotive radar analysis using a cluster-type supercomputer with multiple GPUs. An analysis region was divided into blocks, which were allocated to GPUs. The start time of the operation of each GPU was controlled according to radio wave propagation from a radiation antenna. The proposed method reduced the total simulation time by approximately 34% compared to a conventional method.

Keywords: radar, FDTD, GPU, parallel computation, supercomputer

Classification: Antennas and Propagation

References

1 Introduction

The finite-difference time-domain (FDTD) method [1] is a technique for the sequential calculation of electromagnetic fields by discretizing Maxwell’s equations. Therefore, electromagnetic field components are arranged on a space grid. The cell size is typically less than 1/10 of the wavelength in the FDTD method with a second-order finite difference approximation in time and space.

Automotive radar analysis performed using a cluster-type supercomputer with GPUs requires tens of billions of cells and terabytes of memory, and the analysis time is several days to several weeks. Therefore, it is necessary to accelerate the FDTD simulation to improve the usability and accessibility of large-scale radar analysis.

The conventional techniques for accelerating the FDTD simulation include (1) devising the calculation principle of the FDTD method, (2) improving computational performance, and (3) improving calculation algorithms.

The approaches for devising the calculation principle of the FDTD method include changing the cell size [2] and dividing an analysis domain [3]. The disadvantage of these approaches is that the placement of an analysis target is limited in the computational model, which can compromise versatility and increase calculation errors.

Computational performance has been improved using CPUs with high clock speeds, multiple CPUs, GPUs [4], and a cluster supercomputer with multiple GPUs. The disadvantage of these methods is that the use of large-scale computer equipment can be considerably expensive depending on the usage time.

The methods for improving calculation algorithms are broadly classified into three types: (i) the parallel FDTD method [4], (ii) distributed FDTD method [5], and (iii) parallel and distributed FDTD method [6].

When large-scale analysis is conducted using the FDTD method, parallel and distributed processing is performed using a cluster-type supercomputer with multiple GPUs. This significantly improves the calculation speed. However, the queuing time for the synchronization process increases with the communication load between nodes on the cluster-type computer. Subsequently, the effect of acceleration due to parallel computing is considerably reduced.

This study developed a method of accelerating parallel and distributed calculation by reducing the internode communication load for synchronous processing based on the features of automotive radar analysis without reducing calculation accuracy. An analysis area was divided into blocks along the longitudinal direction. The blocks were assigned to GPUs to control the start time of the operation of each GPU according to radio wave propagation from a radiating antenna. The proposed method improves the efficiency of the existing FDTD method without changing the computational principles or hardware.
2 Problem statement

General large-scale analysis is conducted using the FDTD method. An analysis region is divided into blocks, which are allocated to GPUs with multiple nodes. At each time step, it is necessary to exchange and synchronize the electric and magnetic field components on the boundary surfaces of adjacent blocks. As the number of boundary surfaces increases considerably with the scale of analysis, the amount of internode communication data for boundary processing increases significantly.

The factors that prevent the acceleration of parallel and distributed FDTD calculation are examined by theoretically determining the calculation time per time step, $T$ [s/step]. $T$ is expressed by Eq. (1) and Eq. (2) for the standard FDTD and FDTD methods [2, 4], respectively.

\[
T = \max \left( \frac{39N^3}{pF}, \frac{51 \times 4 \times N^3}{pB} \right) + \frac{\alpha \times 4 \times N \times (\frac{N}{m} + \frac{N}{n})}{pM} + T_d \quad (1)
\]

\[
T = \max \left( \frac{75N^3}{pF}, \frac{75 \times 4 \times N^3}{pB} \right) + \frac{\alpha \times 8 \times N \times (\frac{N}{m} + \frac{N}{n})}{pM} + T_d \quad (2)
\]

Here, the size of the analysis region is $N \times N \times N$, and a two-dimensional division is performed using $p = m \times n$ node computers. $F$ [Flops] is the floating-point arithmetic performance of the computer, $B$ [bps] is the memory bandwidth, $M$ [bps] is the network bandwidth, $T_d$ [s] is the communication delay time, $\alpha$ is the number of boundaries per unit, and the data type is a single-precision floating-point number (4 bytes). According to Eq. (1) or Eq. (2), the network bandwidth strongly affects the simulation time. In general, the network bandwidth is significantly smaller than the memory bandwidth (in the case of TSUBAME 3.0, it is approximately 7 times smaller; $B = 732$ [Gbps], $M = 100$ [Gbps]).

3 Proposed method

As shown in Fig. 1(a), the propagation analysis of an automotive radar is performed over an elongated region along a road. On the basis of this feature, this study proposes a method of accelerating the FDTD simulation specialized for automotive radar analysis. In the proposed method, the analysis region is divided into blocks along the longitudinal direction. The blocks are allocated to GPUs to control the start time of the operation of each GPU according to radio wave propagation from an antenna.

The FDTD method initiates the calculation for radar wave propagation from the antenna at the start of the simulation. Figure 1(c) shows the conventional method, in which the start time of the operation of each GPU is not controlled, i.e., the calculation at each GPU is simultaneously initiated. In contrast, in the proposed method, the calculation at the GPUs is not started and the synchronization process is paused at the start of the simulation. When the radar wave reaches the boundary surface and the electric field value of the radar wave exceeds a predetermined threshold, the calculation at the GPU for the adjacent block is initiated along with the synchronization process (see Fig. 1(b)).

This makes it possible to reduce the number of contacted GPUs and make the number and area of boundary surfaces smaller than those of the conventional method.
Thus, the amount of communication data between nodes can be reduced. In addition, the computational load of the synchronization process can be reduced by pausing the computation at the GPUs where radar waves have not yet arrived. Therefore, the proposed method can accelerate the FDTD simulation for the propagation analysis of the automotive radar.
4 Validity verification

4.1 Simulation conditions

Weak scaling measurement is performed to quantitatively verify the effectiveness of the proposed method. Weak scaling measurement is a method of fixing the scale of the problem solved by each GPU, and it can examine the change in the simulation time vs. the number of GPUs.

In the verification, the analysis region is divided into blocks along the longitudinal direction, and they are allocated to each GPU. The conventional method shown in Fig. 1(c) is assumed to be the baseline method for this verification. The threshold for starting the calculation at each GPU is set as $10^{-6}$ V/m (maximum signal-to-noise ratio: $-157$ dB). This value is considered to be sufficiently smaller than the maximum signal strength, and calculation accuracy can be ensured.

Table I lists the calculation conditions and the specifications of the computer used for the verification. The frequency of the wave radiated from the antenna is 24 GHz, which is the same as that of an actual automotive radar. The analysis region has a maximum range of 112 m, and 100 GPU units are used.

4.2 Result

The verification results are shown in Fig. 2(a). The simulation time of the proposed method is smaller than that of the baseline method, and the difference increases with the number of GPUs (analysis scales). The proposed method reduces the simulation time by approximately 34% at 100 GPU units compared to the baseline method.

Figure 2(b) shows the acceleration rate, which is defined by Eq. (3).

$$R_a = \frac{T_c}{T_p} \times 100 \quad (3)$$

Here, $R_a$ [%] is the acceleration rate and $T_c$ [s] and $T_p$ [s] are the simulation times of the conventional and proposed methods, respectively.

The maximum acceleration rate is 160% at 64 GPU units. Accordingly, the simulation time can reduce from seven days to four days for a large-scale automotive radar analysis. In contrast, there is another simulation load that cannot be reduced by the proposed method. That is the load due to the placement of each GPU in the network on the supercomputer when the number of GPUs is large. In this case, the acceleration rate was lower at 100 GPU units than at 64 GPU units.

| Table I. Simulation conditions |
|-------------------------------|---|
| Frequency | 24 GHz |
| Analysis region | (896 × n) × 448 × 448 [cells] |
| | (112 [m]−9 [m])×0.6 [m]×0.6 [m] |
| Cell size | 1.25 [mm] (≈1/10λ) |
| Method | FDTD(2,4) |
| CFL | 0.136 |
| Time step | $5.68 \times 10^{-13}$ [s] |
| Radiation source | 1/2 λ dipole antenna, continuous sine wave |
| Number of calculations | 6525 × n [steps] |
| Absorber | PML 32 layers, $R_0 = 1.0 \times 10^{-22}$, $M = 4$ |
| Number of GPUs | n [units] |
| GPU | NVIDIA TESLA P100 for NVLink-Optimized servers ×4 |
| RAM | 256 [GB] (DDR4-2400 32 [GB] ×4) |
| Network | 100 [Gbps] (Intel Omni-Path Architecture FHI) |
5 Conclusion

This study proposed a method of accelerating the FDTD simulation specialized for automotive radar analysis. An analysis region was divided into blocks in the longitudinal direction. These blocks were allocated to GPUs to control the start time of the operation of each GPU according to radio wave propagation from a radiating antenna. The findings of this study are as follows: The proposed method reduced the synchronization process and significantly decreased the simulation time compared to the conventional method. The total simulation time for large-scale automotive radar analysis decreased by approximately 34% at 100 GPU units compared to the conventional method.
Deep-learning-based sequential phishing detection

Yuji Ogawa\(^1\), Tomotaka Kimura\(^1, a)\), and Jun Cheng\(^1\)
\(^1\) Graduate School of Science and Engineering, Doshisha University, 1–3 Tatara Miyakodani, Kyotanabe-shi, Kyoto 610–0321 Japan
\(a)\) tomkimur@mail.doshisha.ac.jp

Abstract: In this paper, we propose a deep-learning-based sequential phishing detection to improve the security and speed of the phishing detection. In our proposed method, phishing websites are detected in three phases: the URL, domain, and HTML analysis phases. In these phases, URLs, DNS records, and HTML contents are input to CNN-BiLSTMs (Convolutional Neural Network-Bidirectional Long Short Term Memory), respectively. Through experiments, we show that our proposed method is faster than the existing detection method, in which URLs and HTML contents are input to a CNN-BiLSTM simultaneously.

Keywords: deep learning, phishing attack, URL analysis, domain analysis, HTML analysis

Classification: Internet

References

1 Introduction
In recent years, the development of Internet technology has brought about many advantages. The damage, however, caused by cyber attacks, such as phishing attacks, has been increasing [1]. In a phishing attack, the URL of a phishing website is
placed in an e-mail or website to induce target users to access it. When the target user accesses a phishing website, misunderstands it to be a benign site, and enters personal information (e.g., a bank account number), the attacker steals it. The attacker then abuses the stolen personal information, which causes serious damage (e.g., by performing a fraudulent money transfer).

To combat phishing attacks, blacklist-based detection methods have been used to date. In general, with blacklist-based detection methods, the execution speed is high and the FPR (False Positive Rate) is very low. However, when phishing websites are updated frequently, the blacklist-based phishing detection methods cannot respond because the blacklists need to be updated manually [2]. Therefore, deep-learning-based detection methods are attracting attention because deep learning can automatically extract the features of phishing websites and can respond to changes.

Some deep-learning-based detection methods have been considered in the literature. In [3], the authors considered a URL-based detection method that uses only the URLs of websites as input. The URL-based detection method is highly secure because it can determine whether a website is a phishing website without downloading the contents of the website. In addition, the execution speed of this detection method is high because it uses only URLs. However, its weakness is that its detection accuracy is low. In [4], the authors proposed Web2Vec, which uses URLs, HTML contents, and DOM (Document Object Model) structures as input for phishing detection. Because Web2Vec uses the information from the website contents, its detection accuracy is higher than that of the URL-based detection method. However, Web2Vec is less secure than the URL-based detection method because it requires the download of contents. Moreover, because it uses HTML contents and DOM structures as inputs, Web2Vec requires more pre-processing time than URL-based detection methods.

In this paper, we propose a deep-learning-based sequential method for phishing detection to improve the security and speed of the phishing detection. In our proposed method, phishing websites are detected in three phases: the URL analysis phase, domain analysis phase, and HTML analysis phase. In the URL analysis phase, a neural network with the URL of a website as an input determines whether this URL is the URL of a phishing website. The domain analysis phase uses a neural network with domain registration information, such as DNS information, as input. In the HTML analysis phase, a neural network with HTML and DOM information as input is used to make a decision. Through experiments, we show that our proposed method reduces the downloading of contents and is faster than the existing detection method.

2 Proposed sequential phishing detection method

Figure 1 shows a flowchart of our sequential phishing detection method, which consists of three phases. First, in the URL analysis phase, the URL of the target website is tokenized to a character vector $x_C$ and a word vector $x_W$. Each of these vectors $x_C$ and $x_W$ is then input into a CNN-BiLSTM (Convolutional Neural Network-Bidirectional Long Short Term Memory). The outputs of the two CNN-BiLSTMs are combined, and input into the fully connected layer with activation
functions, which outputs \( f_U(x_C, x_W) \) (\( 0 \leq f_U(x_C, x_W) \leq 1 \)). If \( f_U(x_C, x_W) \) is high, the target website is likely to be a phishing website; otherwise, it is likely to be benign. Moreover, if \( f_U(x_C, x_W) \) is close to 0.5, it is difficult to determine whether the target website is a phishing website or a benign one. Therefore, our proposed detection method uses a threshold parameter \( \alpha \) (\( 0 < \alpha < 0.5 \)) as follows:

- \( f_U(x_C, x_W) < \alpha \): The target website is determined to be benign.
- \( f_U(x_C, x_W) > 1 - \alpha \): The target website is determined to be a phishing website.
- \( \alpha \leq f_U(x_C, x_W) \leq 1 - \alpha \): The URL analysis is inconclusive, so that the method proceeds to the domain analysis phase.

In the domain analysis phase, DNS information is used for phishing detection. It is well-known that the features of DNS information differ between benign and phishing websites [5], and therefore DNS information is expected to be useful for phishing detection. In addition, domain analysis is secure because there is no need to access the target website to obtain the DNS information. Our sequential detection method uses DNS A records, which can be obtained from the URL of the target website by a query to a DNS server. Following the URL analysis phase, the DNS A record of the target website is tokenized to a character vector \( y_C \) and a word vector \( y_W \). Each of these vectors is input into a CNN-BiLSTM, and their outputs are input to the fully connected layer with activation functions, which outputs \( f_D(y_C, y_W) \). If \( f_D(y_C, y_W) \) is high, the target website is likely to be a phishing website; otherwise, it is likely to be benign. If \( f_D(y_C, y_W) \) is close to 0.5, it is difficult to determine whether the target website is a phishing website or a benign one. Therefore, the sequential phishing detection method uses a threshold parameter \( \beta \) (\( 0 < \beta < 0.5 \)) as follows:

- \( f_D(y_C, y_W) < \beta \): The target website is determined to be benign.
- \( f_D(y_C, y_W) > 1 - \beta \): The target website is determined to be a phishing website.
- \( \beta \leq f_D(y_C, y_W) \leq 1 - \beta \): The domain analysis is inconclusive, so that the method proceeds to the HTML analysis phase.

Finally, in the HTML analysis phase, the contents of the target website are downloaded. The HTML contents and DOM structures are extracted from the
downloaded contents of the target website. As in [4], for HTML content, vectors $z_W$ and $z_S$, which are tokenized into word units and sentence units, respectively, are input to two CNN-BiLSTMs. For DOM structures, a vector $z_D$, which is the sequence of HTML tags tokenized to word units, is input to another CNN-BiLSTM. The outputs of the three CNN-BiLSTMs are input to the fully connected layer with activation functions, which outputs $f_H(z_W, z_S, z_D)$. If $f_H(z_W, z_S, z_D) \geq 0.5$, the target website is determined to be a phishing website; otherwise, it is determined to be benign.

3 Performance evaluation

To evaluate our sequential phishing detection method, we used a dataset [4], that contains the URLs, HTML contents, and DOM structures. We collected the DNS information on the URLs in the dataset. Because the DNS information was not available for some URLs, we removed the data corresponding to those URLs from the dataset. In our experiments, the total number of data is 36,294. Of these, the numbers of the training and test data were 32,675 and 3,619, respectively. An example of the data is shown in Table I.

In our phishing detection method, the numbers of training epochs performed for the URL, domain, and HTML analysis phases were 10, 100, and 10, respectively. To evaluate the performance, we show the results of Web2Vec and the individual performance of the URL, domain, and HTML analyses. We used the same parameters for Web2Vec as those used in [4]. We used a computer with a Xeon Gold 6242 CPU and an NVIDIA Quadro P6000 GPU.

Figures 2 (a) and (b) show the accuracy and FPR, respectively. Accuracy and FPR are defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}, \quad \text{FPR} = \frac{FP}{TN + FP},$$

where TP and FP denote the numbers of phishing websites and benign websites, respectively, classified as phishing sites, and TN and FN denote the numbers of benign websites and phishing websites, respectively, classified as benign websites. Although Web2Vec achieved the best performance with respect to both accuracy and FPR, the performance of our proposed method is comparable to that of Web2Vec. Of the analysis, the HTML analysis achieves good performance, whereas the domain analysis is inferior to other analysis. This result implies that, if the performance of the domain analysis could be improved, the overall performance of our proposed method would improve. We leave the improvement of the domain analysis for future work.

Table I. Example of phishing website data.

<table>
<thead>
<tr>
<th>Category</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>URL</td>
<td><a href="http://creative***.com/">http://creative***.com/</a></td>
</tr>
<tr>
<td>HTML Contents</td>
<td>Inspiration Resources and Tutorials . . .</td>
</tr>
<tr>
<td>DOM</td>
<td>html head meta meta link meta . . .</td>
</tr>
<tr>
<td>DNS</td>
<td>creative***.com. 113 IN A 165.227.82.***</td>
</tr>
</tbody>
</table>
Figure 2 (c) shows the computation time for discriminating the phishing websites included in the test dataset. As threshold $\alpha$ increases, the computation time of our proposed method decreases. For large $\alpha$, the computation time of our proposed method is comparable to that of the URL analysis. Moreover, for all values of $\alpha$, our proposed method is faster than Web2Vec. These results indicate that our proposed method can detect phishing websites quickly.

Finally, Fig. 2 (d) shows the determination ratio of the URL, domain, and HTML analyses of our proposed method. The determination ratio is defined as the fraction of all determinations that are performed by the URL, domain, and HTML analyses of the method. For all threshold values, the majority of the determination is performed by the URL analysis. For a small threshold value, about 10% of the determinations are performed by the domain analysis. Therefore, the HTML analysis is rarely performed. This is the reason for the high speed of our proposed method.

4 Conclusion

In this paper, we proposed a sequential phishing detection method based on deep learning to improve the security and detection speed, and evaluated its performance in experiments. The experiments showed that our proposed method outperforms an existing phishing detection method (i.e., Web2Vec) with respect to execution speed. However, the accuracy of our proposed method is inferior to that of Web2Vec. Therefore, we will improve this accuracy in future work.

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Performance improvement of faster-than-Nyquist single-carrier MIMO signaling considering the effects of colored noise

Yuta Kumagai¹, Atsuya Nakamura¹, Shuhei Saito¹, Hirofumi Suganuma¹, Keita Kuriyama², Yu Ono², Hayato Fukuzono², Masafumi Yoshioka², and Fumiaki Maehara¹. a)

¹ Graduate School of Fundamental Science and Engineering, Waseda University, 3–4–1 Ohkubo, Shinjuku-ku, Tokyo 169–8555, Japan
² NTT Access Network Service Systems Laboratories, Nippon Telegraph and Telephone Corporation, 1–1 Hikarino-oka, Yokosuka-shi, Kanagawa 239–0847, Japan
a) fumiaki_m@waseda.jp

Abstract: This study proposes a faster-than-Nyquist (FTN) single-carrier multiple-input multiple-output (MIMO) signaling scheme considering the effects of colored noise. In this approach, frequency-domain equalization (FDE) is considered as a practical receiver. Moreover, since FTN signaling generally induces colored noise, the proposed scheme considers its impact on FDE weight generation for improved detection accuracy of FTN-MIMO signaling. The effectiveness of the proposed scheme is demonstrated in terms of both bit error rate (BER) and throughput via the compression factor parameters and MIMO antenna configuration through computer simulations.

Keywords: faster-than-Nyquist (FTN) signaling, multiple-input multiple-output (MIMO), single-carrier with frequency-domain equalization (SC-FDE), colored noise, throughput

Classification: Wireless Communication Technologies

References

1 Introduction

Faster-than-Nyquist (FTN) signaling is a promising technique for achieving high spectral efficiencies [1, 2, 3, 4] because it offers higher transmission rates than Nyquist signaling owing to non-orthogonal transmission that compresses the symbol period in the time domain while allowing inter-symbol interference. Therefore, FTN signaling is suitable for application to mobile communications and broadcasting satellite systems [2, 4].

To further improve spectral efficiency, it is effective to combine FTN signaling with a multiple-input multiple-output (MIMO) system to enable simultaneous transmission of multiple streams and has been investigated to some extent in reported works [3, 5, 6, 7]. In [5], the Mazo limit of FTN-MIMO signaling was discussed first, which indicated the potential for capacity enhancement. Then, a capacity analysis of FTN-MIMO signaling was presented under the assumption of flat Rayleigh fading channels in [6], which suggested applicability to future wireless communications systems. In [7], a single carrier with frequency-domain equalization (SC-FDE) was introduced to realize FTN-MIMO signaling with low computational complexity at the receiver, and its effectiveness was demonstrated under multipath fading channels. However, in [7], white noise was assumed in the FDE weight generation, even though colored noise is generally induced by faster sampling which is specific to FTN signaling [3]. Therefore, performance improvements can be realized by considering the effects of colored noise in FTN-MIMO signaling.

Considering this background, we propose a novel FTN-MIMO signaling scheme by accounting for the effects of colored noise. The main feature of the proposed scheme is to improve detection accuracy at the receiver, so the impact of colored
noise induced by FTN signaling is taken into account during derivation of the FDE weights. Specifically, the frequency-domain noise correlation matrix is calculated in advance and incorporated into the FDE weight matrix based on the minimum mean square error (MMSE) criterion. The effectiveness of the proposed scheme is evaluated and demonstrated in terms of both bit error rate (BER) and throughput via computer simulations using the compression factor parameters and MIMO antenna configuration.

2 Proposed scheme

Figure 1 illustrates the system configuration of the FTN-MIMO signaling scheme employing SC-FDE, where \( N_t \) and \( N_r \) denote the numbers of transmitting and receiving antennas, respectively. At the transmitter, a guard interval (GI) is inserted in the modulated signals of each stream to prevent inter-block interference, and such signals are subsequently pulse-shaped using a low-pass filter and transmitted from each antenna. At the receiver, after applying a matched filter to the received signals and eliminating the GI, FDE is performed to suppress both inter-symbol and inter-stream interferences; thereafter, the equalized signals are demodulated.

The pulse-shaped transmit signal of the \( p \)-th stream \( s_p(t) \) \((1 \leq p \leq N_t)\) is given as

\[
s_p(t) = \sum_{n} a_p[n] g(t - n\tau T),
\]
where \( T, \tau (0 < \tau \leq 1), a_p[n], \) and \( g(t) \) are the symbol period under the Nyquist criterion, compression factor, modulated signal with an \( N_G \)-length GI, and pulse-shaping filter, respectively. It is noted that the transmission rate of FTN signaling can be increased by up to \( 1/\tau \) times that of Nyquist signaling \((\tau = 1)\). At the receiver, the received signal from the \( q \)-th antenna \( r_q(t) \) \((1 \leq q \leq N_r)\) is passed through a matched filter \( g'(-t) \) and sampled at intervals of \( \tau T \). In multipath fading channels, especially those in mobile broadband communication systems, the signal received from the matched filter \( y_q[n] \) is represented as

\[
y_q[n] = \int_{-\infty}^{\infty} r_q(t) g'(-(t - n\tau T)) \, dt = \sum_{p=1}^{N_t} \sum_{l=0}^{L-1} \sum_{m=-\nu}^{\nu} h_{qp}[l] y[n - (l + m)] a_p[m] + \eta_q[n],
\]
where \( h_{qp}[l] \) is the channel impulse response between the \( p \)-th transmitting and \( q \)-th receiving antennas, \( L \) is its effective length, \((2\nu + 1)\) corresponds to the tap length comprising the transmitting and receiving filters. The impulse response consisting

![Figure 1. System configuration of MIMO-FTN signaling.](image)
of the transmitting and receiving filters $\gamma[n - m]$ and colored noise passed through the matched filter $\eta_q[n]$ are defined as
\begin{align}
\gamma[n - m] &= \int_{-\infty}^{\infty} g(t - m\tau T)g^\ast(-(t - n\tau T)) \, dt, \\
\eta_q[n] &= \int_{-\infty}^{\infty} n_q(t)g^\ast(-(t - n\tau T)) \, dt,
\end{align}
where $n_q(t)$ is white Gaussian noise with power $\sigma_n^2$. Using Eq. (2), the received signal vector for each $N_F$-length block can be expressed as $y = \mathbf{H} \mathbf{a} + \mathbf{\eta}$, where $\mathbf{a} = [a^T_0, a^T_1, \ldots, a^T_{N_F-1}]^T \in \mathbb{C}^{N_t N_F}$ and $\mathbf{\eta} = [\eta^T_0, \eta^T_1, \ldots, \eta^T_{N_F-1}]^T \in \mathbb{C}^{N_r N_F}$ are the modulated signal and colored noise vectors, respectively; $\mathbf{H} \in \mathbb{C}^{N_r N_F \times N_t N_F}$ and $\mathbf{I} \in \mathbb{C}^{N_t N_F \times N_t N_F}$ are block circulant matrices populated with tap coefficients $h[\cdot]$ and $\gamma[\cdot]$, respectively. The received signals of each antenna are converted to frequency-domain signals via fast Fourier transform (FFT) processing, and FDE is conducted using a weight matrix $\mathbf{W} \in \mathbb{C}^{N_r N_F \times N_t N_F}$. Thereafter, inverse fast Fourier transform (IFFT) processing is performed to obtain the time-domain signals. The time-domain signal vector after FDE $\hat{\mathbf{a}} \in \mathbb{C}^{N_t N_F}$ is represented by [8]
\begin{align}
\hat{\mathbf{a}} &= (\mathbf{F}^H_{N_F} \otimes \mathbf{I}_{N_t}) \mathbf{W}(\mathbf{F}_{N_F} \otimes \mathbf{I}_{N_r}) y \\
&= (\mathbf{F}^H_{N_F} \otimes \mathbf{I}_{N_t}) \mathbf{W}(\mathbf{F}_{N_F} \otimes \mathbf{I}_{N_r}) \mathbf{H} \mathbf{a} + (\mathbf{F}^H_{N_F} \otimes \mathbf{I}_{N_t}) \mathbf{W}(\mathbf{F}_{N_F} \otimes \mathbf{I}_{N_r}) \mathbf{\eta} \\
&= (\mathbf{F}^H_{N_F} \otimes \mathbf{I}_{N_t}) \mathbf{W} \mathbf{A} (\mathbf{F}_{N_F} \otimes \mathbf{I}_{N_r}) \mathbf{a} + (\mathbf{F}^H_{N_F} \otimes \mathbf{I}_{N_t}) \mathbf{W}(\mathbf{F}_{N_F} \otimes \mathbf{I}_{N_r}) \mathbf{\eta},
\end{align}
where $\otimes$ is the Kronecker product, $\mathbf{I}_{N_t} \in \mathbb{C}^{N_t \times N_t}$ and $\mathbf{I}_{N_r} \in \mathbb{C}^{N_r \times N_r}$ are identity matrices, and $\mathbf{F}_{N_F} \in \mathbb{C}^{N_t N_F \times N_t N_F}$ is the $N_F$-point FFT. In Eq. (5), we utilize the fact that the block circulant matrix $\mathbf{H} \mathbf{I}$ can be block-diagonalized as follows [9]:
\begin{align}
\mathbf{H} \mathbf{I} &= (\mathbf{F}^H_{N_F} \otimes \mathbf{I}_{N_t}) \mathbf{A} (\mathbf{F}_{N_F} \otimes \mathbf{I}_{N_r}) \\
&= (\mathbf{F}^H_{N_F} \otimes \mathbf{I}_{N_t}) \mathbf{\text{diag}}(\mathbf{A}_0, \ldots, \mathbf{A}_{N_F-1}) (\mathbf{F}_{N_F} \otimes \mathbf{I}_{N_r}),
\end{align}
where $\mathbf{A}_k \in \mathbb{C}^{N_r \times N_t}$ ($0 \leq k \leq N_F - 1$) is the frequency response matrix of the $k$-th subchannel.

Assuming the MMSE as the equalization criterion, the weight matrix $\mathbf{W}_{\text{MMSE}}$ is given as
\begin{align}
\mathbf{W}_{\text{MMSE}} &= \arg \min_{\mathbf{W}} \mathbb{E} [\|\hat{\mathbf{a}} - \mathbf{a}\|^2] \\
&= \sigma_n^2 \mathbf{A}^H \left( \sigma_n^2 \mathbf{A} \mathbf{A}^H + (\mathbf{F}_{N_F} \otimes \mathbf{I}_{N_r}) \mathbb{E}[\mathbf{\eta} \mathbf{\eta}^H] (\mathbf{F}_{N_F}^H \otimes \mathbf{I}_{N_t}) \right)^{-1},
\end{align}
where $\sigma_n^2$ denotes the transmitted power. If $\mathbf{\eta}$ is the white noise, then $\mathbb{E}[\mathbf{\eta} \mathbf{\eta}^H] = \sigma_n^2 \mathbf{I}_{N_r N_F}$. Thus, the weight matrix can be represented as a block diagonal matrix $\text{diag}(\mathbf{W}_0, \mathbf{W}_1, \ldots, \mathbf{W}_{N_F-1})$. In this case, the weight matrix of the $k$-th subchannel $\mathbf{W}_{k, \text{white}} \in \mathbb{C}^{N_r \times N_t}$ is expressed as [7]
\begin{align}
\mathbf{W}_{k, \text{white}} &= \mathbf{A}_k^H \left( \mathbf{A}_k \mathbf{A}_k^H + \frac{\sigma_n^2}{\sigma_q^2} \mathbf{I}_{N_r} \right)^{-1},
\end{align}
However, $\mathbf{\eta}$ generally represents the colored noise in FTN signaling [3], and the weight matrix of Eq. (7) is not block diagonal, thereby failing to achieve computational reduction, which is one of the features of FDE. Therefore, to ensure
Subchannel-wise operation [3], we approximate \((F_{NF} \otimes I_{Nr})E[\eta \eta^H](F_{NF}^H \otimes I_{Nr})\) as a block diagonal matrix. Then, the weight matrix of the \(k\)-th subchannel \(W_{k,\text{colored}} \in \mathbb{C}^{N_t \times N_r}\) is represented as follows:

\[
W_{k,\text{colored}} = A_k A_k^H \left( \frac{1}{\sigma^2} \Phi_k \right)^{-1},
\]

where \(\Phi_k \in \mathbb{C}^{N_r \times N_r}\) is the noise correlation matrix in the frequency domain. Considering that the noises between the different antennas are independent of each other, the \((q, q')\) element of \(\Phi_k\) is calculated as [3]

\[
\phi_{k,q,q'} = \mathbb{E} \left[ \left( \frac{1}{\sqrt{N_F}} \sum_{m=0}^{N_r-1} \eta_q[m] e^{-j 2\pi k m / N_F} \right) \left( \frac{1}{\sqrt{N_F}} \sum_{m=0}^{N_r-1} \eta_{q'}[m] e^{-j 2\pi k m / N_F} \right)^* \right]
\]

\[
= \frac{\sigma^2}{N_F} \sum_{n=0}^{N_r-1} \sum_{m=0}^{N_r-1} \gamma \left[ n - m \right] e^{-j 2\pi \left( n - m \right) k / N_F} \quad (q = q')
\]

\[
= 0 \quad (q \neq q')
\]

(10)

Here, the summation in Eq. (10) depends only on the transmitting and receiving filters and can therefore be calculated in advance.

3 Numerical results

This section presents a demonstration of the effectiveness of the proposed FTN-MIMO scheme in terms of both BER and throughput, and Table I lists the simulation parameters. In the performance evaluations, a root-raised cosine (RRC) filter with a roll-off factor of \(\alpha = 0.5\) was used as the pulse-shaping filter [5]. The 3GPP TDL-C model was assumed for radio propagation, where the delay spread was set to 93 ns at a carrier frequency of \(f_c = 6\) GHz in the UMi street canyon scenario [10]. The GI length \(N_G\) was greater than the filter and channel delays; therefore, there were no effects of inter-block interference.

Figure 2(a) shows the BER performance versus average carrier-to-noise ratio (CNR) in 2 \(\times\) 2 and 4 \(\times\) 4 MIMO, where QPSK modulation was assumed. From Fig. 2(a), it can be seen that, in Nyquist signaling, the proposed scheme based on Eq. (9) achieves the same BER performance as the traditional scheme based on Eq. (8); this is because the impact of noise can be regarded as white. However, it is observed that, in FTN signaling, the consideration of colored noise in the proposed scheme improves the BER performance, irrespective of the MIMO antenna configuration. Moreover, the performance gap between the proposed and traditional

### Table I. Simulation parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier frequency (f_c) / Bandwidth (B)</td>
<td>6 GHz / 20 MHz</td>
</tr>
<tr>
<td>Sampling period (T_{sam}) / Modulation</td>
<td>7.5 ns / QPSK, 16QAM</td>
</tr>
<tr>
<td>Number of transmitting antennas (N_t)</td>
<td>1, 2, 4</td>
</tr>
<tr>
<td>Number of receiving antennas (N_r)</td>
<td>1, 2, 4</td>
</tr>
<tr>
<td>Number of FFT points (N_F) / GI length (N_G)</td>
<td>2048 / 512</td>
</tr>
<tr>
<td>Pulse shaping filter / Roll-off factor (\alpha)</td>
<td>Root-raised cosine (RRC) / 0.5</td>
</tr>
<tr>
<td>Channel model / Delay spread</td>
<td>3GPP TDL-C [10] / 93 ns</td>
</tr>
</tbody>
</table>
Figure 2 shows the throughput performance versus average CNR, using the proposed FDE based on Eq. (9) and compression factor $r$ set to 0.7. Here, the throughput is calculated by \[ \text{Throughput} = \frac{N_F}{N_F + N_G} \sum_{p=1}^{N_t} \log_2 M \left( \frac{1}{1 + \alpha} \right) \cdot \left( 1 - H(P_p) \right), \] where $M$ is the modulation level, $H(\cdot)$ is the binary entropy function, and $P_p$ is the uncoded BER of the $p$-th stream that is obtained from computer simulations. From Fig. 2(b), it is observed that the throughput performance is improved with increase in the MIMO antenna configuration regardless of the modulation scheme because of the large number of streams. Moreover, even in MIMO cases such as $2 \times 2$ and $4 \times 4$, FTN signaling overcomes Nyquist signaling owing to the higher transmission rate from compression of the symbol period.

4 Conclusion

In this study, we proposed a novel FTN-MIMO signaling scheme considering the effects of colored noise. In the proposed method, SC-FDE is adopted for trans-
mission, and the impact of colored noise induced by FTN signaling is taken into account during FDE weight generation for improving detection accuracy. Numerical simulations were performed, and the results showed that considering colored noise in the FDE weights improves BER performance regardless of the MIMO antenna configuration. Moreover, even in MIMO cases, FTN signaling is superior to Nyquist signaling in terms of throughput owing to the higher transmission rate achieved by compression of the symbol period.