

Denoising CNN Based Channel Estimation for Vehicular OTFS Communication System

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Abstract—The orthogonal time-frequency space (OTFS) technique can convert the double dispersive channel in the time-frequency (TF) domain into a time-invariant channel in the delayed-Doppler (DD) domain through a series of two dimensional transformations, which shows promising applications in high-speed vehicular communication scenarios. As a key part in OTFS system, conventional pilot-based channel estimation schemes have obvious drawbacks, such as low accuracy and poor robustness to mobility. In this paper, we propose a denoising convolutional neural network (DCNN) based channel estimation scheme in OTFS system for high-speed vehicular communications by introducing hybrid dilated convolution (HDC) and residual paths into convolutional neural network (CNN). Simulation results show that the DCNN method can achieve fast DD domain channel estimation with lower complexity compared with the conventional schemes. Meanwhile, it is robust to different vehicle speeds while satisfying high accuracy in channel estimation.

Index Terms—OTFS, vehicular communication, channel estimation, OMP

I. INTRODUCTION

Orthogonal time-frequency space (OTFS) technique is currently widely studied in the field of communication. In high-speed mobile vehicular communication scenarios, the Doppler shift and multipath effect of time-varying channels are challengeable, which may lead to poor system bit error rate (BER) and influence the communication performance significantly. As a key part in wireless systems, the channel estimation techniques mainly include three categories, pilot-based, blind and semi-blind channel estimation. Since the latter two have the drawbacks of slow convergence, low accuracy and difficult implementation, they cannot be applied to the fast time-varying channels. Hence, the channel estimation in OTFS communication system is mainly based on pilot signals. Currently, for high-speed mobile scenarios, deep learning (DL) technologies are employed to design efficient and reliable channel estimation schemes with excellent adaptability.

P. Raviteja et al. proposed an embedded pilot-assisted scheme [1] for OTFS channel estimation, where pilot symbols, protection, and data symbols are arranged for each OTFS frame in the delay-Doppler (DD) domain to avoid interference at the receiver. Since the specific embedded pilot symbols are used, OTFS channel estimation is performed within the same frame,

thus minimizing the overhead. [2] also studied the OTFS channel estimation and proposed a pseudo-random noise based scheme in DD domain. The problem of sparse DD channel modeling is studied in [3], and an iterative message passing based DD channel estimation in multi-antenna OTFS communication system is proposed by using OTFS channel symbol coupling. In addition, a ResNet-based OTFS channel estimation was presented in [4]. Owing to the complexity and variability of fast time-varying channels, DL method can be used to characterize the channel features and automatically learn the channel characteristics [5], thus greatly reducing the channel estimation complexity [6].

In this paper, a fast DD domain channel estimation scheme for OTFS communication system in vehicular network is studied in the context of high-speed mobility with the objective of improving the estimation accuracy and reducing the complexity. The orthogonal matching pursuit (OMP) algorithm is combined with denoising convolutional neural network (DCNN) to model the channel estimation as a denoising problem. The fast DD domain channel estimation in high mobility OTFS communication system is presented by using the low complexity convolutional neural network (CNN), which can significantly improve the accuracy of estimation and have good robustness to different moving speeds.

II. SYSTEM MODEL

In this section, we first introduce the model of OTFS communication system in vehicular network and focus the channel estimation problem on noise cancellation. Then, the pilot-based channel estimation scheme and the OMP algorithm are given.

A. OTFS System Model

A quadrature amplitude modulation (QAM) symbol frame of length $M \times N$ is arranged into a two dimensional complex data set with size of $M \times N$, where M and N are the number of delay and Doppler, respectively. The OTFS communication system model is shown in Figure. 1.

The OTFS frame signal $x_{DD}(k, l)$ in the DD domain can be converted into a time-frequency (TF) domain signal $X_{TF}[n, m]$ by Inverse Sin Finite Fourier Transform (ISFFT), which can be

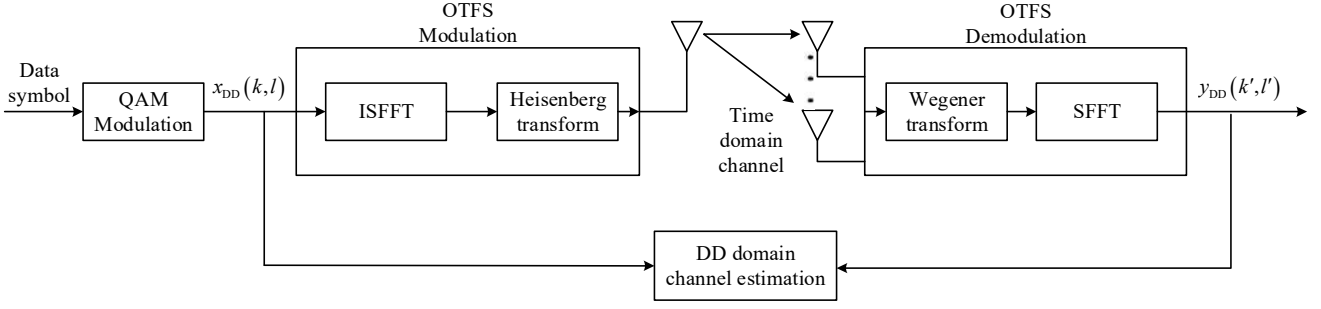


Figure 1. OTFS communication system model.

expressed as

$$X_{\text{TF}}[n, m] = \frac{1}{\sqrt{MN}} \sum_{k=0}^{N-1} \sum_{l=0}^{M-1} x_{\text{DD}}(k, l) e^{j2\pi \left(\frac{nk}{N} - \frac{ml}{M} \right)}. \quad (1)$$

Using Heisenberg transform for $X_{\text{TF}}[n, m]$, the time domain signal $s(t)$ is obtained as

$$s(t) = \sum_{m=-\frac{M}{2}}^{\frac{M}{2}-1} \sum_{n=0}^{N-1} X_{\text{TF}}[n, m] g_{\text{tx}}(t - nT) e^{j2\pi \Delta f (t - nT)}, \quad (2)$$

where $g_{\text{tx}}(t)$ is the time domain transmit pulse shape, T and Δf are the minimum sampling interval and the sampling frequency in the TF domain, respectively [7].

Subsequently, $s(t)$ passes through the double-selective fading channel, and the time domain signal $r(t)$ obtained at the receiver can be expressed as

$$r(t) = \iint h(\tau, \nu) g_{\text{rx}}(t - \tau) e^{j2\pi \nu t} d\tau d\nu + v_n(t), \quad (3)$$

where $v_n(t)$ denotes the time-domain additive Gaussian white noise (AWGN), $h(\tau, \nu)$ is the channel impulse response with τ and ν being the DD domain path delay and Doppler frequency shift, respectively, and shown as

$$h(\tau, \nu) = \sum_{p=1}^P h_p(\tau, \nu) \delta(\tau - \tau_p) \delta(\nu - \nu_p), \quad (4)$$

where P is the multipath number, $\delta(\cdot)$ denotes the Dirac function, $h_p(\tau, \nu)$, τ_p and ν_p represent the channel coefficient, delay and Doppler expansion on the p -th path, respectively.

At the receiver, $r(t)$ undergoes a received pulse matching and the Wegener transform as

$$A_{g_{\text{rx}}}(t, f) = \int g_{\text{rx}}(t - \tau) r(t) e^{-j2\pi f(t - \tau)} dt. \quad (5)$$

where $g_{\text{rx}}(t)$ represents the received pulse shape and $A_{g_{\text{rx}}}(t, f)$ represents the cross-fuzzy function. The two dimensional TF domain signal $Y_{\text{TF}}[n, m]$ can be obtained as

$$Y_{\text{TF}}[n, m] = A_{g_{\text{rx}}}(t, f) \Big|_{t=nT, f=m\Delta f}. \quad (6)$$

Finally, Sim Finite Fourier Transform (SFFT) is applied to $Y_{\text{TF}}[n, m]$ to obtain the two dimensional DD domain received signal $y_{\text{DD}}(k, l)$, which can be interpreted as

$$y_{\text{DD}}(k, l) = \frac{1}{\sqrt{MN}} \sum_{k=0}^{N-1} \sum_{l=0}^{M-1} Y_{\text{TF}}[n, m] e^{-j2\pi \left(\frac{nk}{N} - \frac{ml}{M} \right)}. \quad (7)$$

According to Eq. (4), $h_p(\tau, \nu)$ is the DD channel coefficient corresponding to the p -th path, the input-output relationship Eq. (7) of the OTFS communication system can be rewritten as

$$y_{\text{DD}}(k', l') = \frac{1}{MN} \sum_{p=1}^P \sum_{k=0}^{N-1} \sum_{l=0}^{M-1} x_{\text{DD},p}(k, l) \cdot h_p[(k' - k)_N, (l' - l)_M] + v_n(k', l'), \quad (8)$$

where $(\cdot)_N$ and $(\cdot)_M$ represent the modulus N and M operations, respectively, $x_{\text{DD},p}(k, l)$ denotes the DD domain transmitting signal on the p -th path, $v_n(k', l')$ is AWGN in the DD domain [8].

For the two dimensional DD domain symbol in Eq. (7), it can be given in vector form as

$$\mathbf{y} = \sum_{p=1}^P \mathbf{H}_p \mathbf{x}_{\text{DD},p} + \mathbf{v}, \quad (9)$$

where $\mathbf{x}_{\text{DD},p} \in \mathbb{C}^{MN \times 1}$, $\mathbf{H}_p \in \mathbb{C}^{MN \times MN}$, and $\mathbf{v}$ is AWGN vector.

B. OMP Channel Estimation

The key of the pilot-based channel estimation for OTFS communication system is the placement design of pilot symbol and data symbols. Since the DD domain channel can obtain the full TF diversity gain, we use the traditional pilot scheme [9] to obtain the full channel response. The DD domain signal after inserting the pilot symbol can be written as

$$x[k, l] = \begin{cases} x_{ep}, & k = k_{ep}, l = l_{ep} \\ 0, & k \in [k_{ep} - 2k_{\max}, k_{ep} + 2k_{\max}], \\ & l \in [l_{ep} - l_{\max}, l_{ep} + l_{\max}] \\ x_d, & \text{otherwise} \end{cases} \quad (10)$$

where $k_{\max}$ and $l_{\max}$ are the maximum time delay and Doppler extension in the DD domain, respectively. As seen in Figure. 2, we can embed the pilot symbol x_{ep} at $k=k_{ep}$, $l=l_{ep}$, and the

protection intervals of the pilot symbol by setting zero at $k \in [k_{ep} - 2k_{max}, k_{ep} + 2k_{max}]$ and $l \in [l_{ep} - l_{max}, l_{ep} + l_{max}]$. In this way, we can further take the pilot-based OMP algorithm to estimate the channel [10].

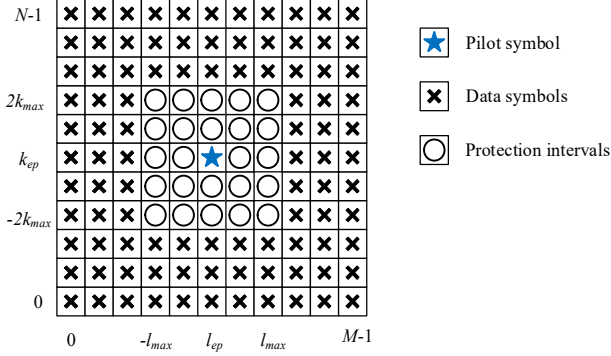


Figure 2. Pilot placement design.

The OMP algorithm for channel estimation in vehicular OTFS communication system is illustrated in Algorithm 1, where the received signal vector $\mathbf{y}$ and the pilot matrix $\mathbf{X}$ are set as the input. In the t -th iteration, the residual $\mathbf{r}_{t-1}$ of the previous iteration is projected onto each column of $\mathbf{X}$. The index s_t of the column with the largest absolute product value is selected and added to the current support S_t and the pilot matrix $\mathbf{X}$ is updated. Subsequently, the least square (LS) method is employed to obtain the t -th estimated vector $\hat{\mathbf{H}}_t$ in the channel matrix, and the residual $\mathbf{r}_t$ is updated. Finally, set the iteration number as $t = t + 1$. Once $t > P$ is satisfied, the iteration is stopped and the newly obtained $\hat{\mathbf{H}}_t$ is the final estimation result $\hat{\mathbf{H}}_{\text{OMP}}$, otherwise the above OMP algorithm operates continuously.

Algorithm 1 OMP based channel estimation

- 1: Input: $\mathbf{X}, \mathbf{y}, P$
- 2: Initialize: $t = 1, S_0 = \emptyset, \mathbf{r}_0 = \mathbf{y}$
- 3: **while** ($t > P$)
- 4: Find column index $s_t = \text{argmax} |\mathbf{X}^H \mathbf{r}_{t-1}|$
- 5: Support update $S_t = S_{t-1} \cup \{s_t\}$,
- 6: Reconstruction of pilot matrix $\mathbf{X}_t = [\mathbf{X}_{t-1}, \mathbf{x}_{S_t}]$
- 7: The least squares algorithm $\hat{\mathbf{H}}_t = \arg \min \|\mathbf{y} - \mathbf{X}_t \hat{\mathbf{H}}\|_2$
- 8: Residual update $\mathbf{r}_t = \mathbf{y} - \mathbf{X}_t \hat{\mathbf{H}}_t$
- 9: $t = t + 1$
- 10: **end**
- 11: Output: OTFS channel estimation matrix $\hat{\mathbf{H}}_{\text{omp}} = \hat{\mathbf{H}}_t$

III. DCNN BASED CHANNEL ESTIMATION

In this section, we formulate the channel estimation in OTFS communication system as a residual noise cancellation problem and propose a DCNN method to enhance the extraction of the

C. DCNN

We design the DCNN based channel estimation scheme in this subsection, which consists of an input layer, two noise cancellation modules and an output layer as shown in Figure. 5.

noise features by introducing hybrid dilated convolution (HDC) into CNN and achieve the noise cancellation through residual paths. Therefore, the DCNN method can improve the channel estimation accuracy specially under low signal-to-noise ratio (SNR). In the following, the DCNN method is introduced in detail.

A. Convolutional Neural Network

CNN can extract features from input data by convolutional operations and reduce model parameters by weight sharing, which has low computational complexity. The basic CNN consists of input layer, convolutional layer, activation function, and output layer, as shown in Figure. 3.

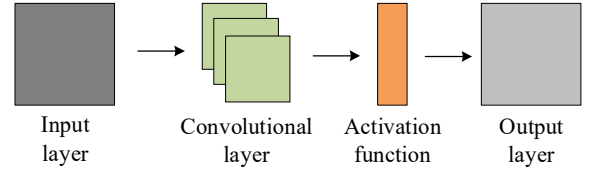


Figure 3. Diagram of CNN.

B. Hybrid Dilated Convolution

CNN has the problem of decreasing resolution and losing local information. Thus, HDC can be introduced in the convolutional layer to solve the above problem by expanding the receptive field [11].

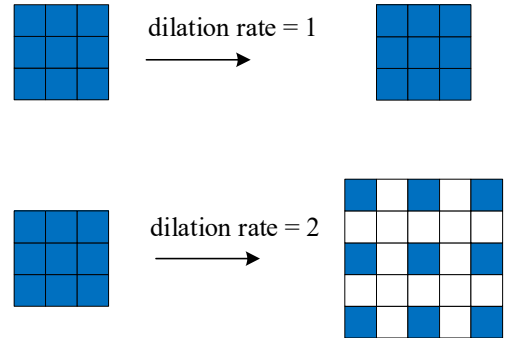


Figure 4. Introduction of dilated convolution.

Take Figure. 4 as an example, for a convolutional kernel of 3×3 size, when the dilation rate is 1, the perceptual field size remains the same. When the dilation rate is 2, the void between adjacent points of the convolutional kernel increase by 1 and the perceptual field size becomes 5×5 . Therefore, when the dilation rates of the two superimposed convolutional layers are set to be 1 and 2, respectively, the perceptual field can be expanded. However, the continuous increase of the dilation rates will result in data loss due to kernel discontinuity. For this case, we can employ HDC when multiple convolutional layers are superimposed in CNN and the dilation rates should not be set as a common divisor greater than 1.

Each noise cancellation module has a residual path and three convolutional layers of 3×3 size, and the expansion dilation rates of these three convolutional layers are set to be 1, 2, and 5, respectively. First, the pre-estimated channel matrix $\hat{\mathbf{H}}_{\text{OMP}}$

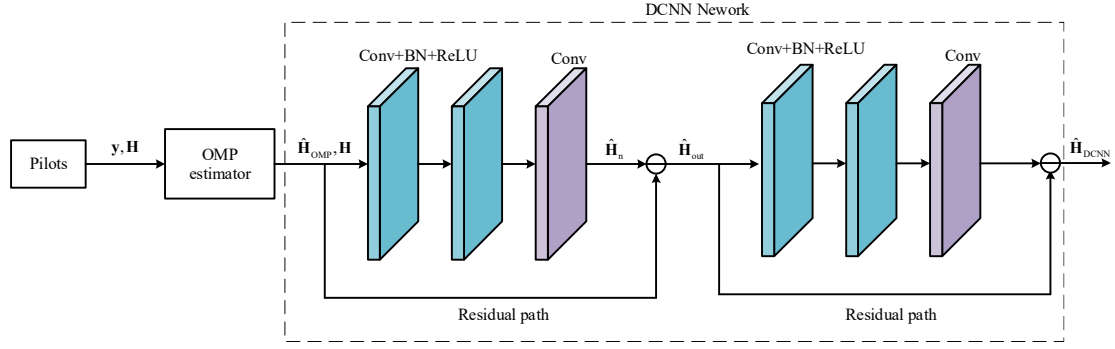


Figure 5. The framework of DCNN

obtained by the OMP algorithm is taken as the input of DCNN, and the real channel matrix $\mathbf{H}$ is used as the label. Through the first noise cancellation module, the DCNN distinguishes the difference between $\hat{\mathbf{H}}_{OMP}$ and $\mathbf{H}$ to achieve the extraction of the noise matrix $\hat{\mathbf{H}}_n$. Subsequently, the channel matrix $\hat{\mathbf{H}}_{out}$ from the output layer of the first noise cancellation module is obtained by subtracting $\hat{\mathbf{H}}_n$ from $\hat{\mathbf{H}}_{OMP}$ through the residual path. Finally, $\hat{\mathbf{H}}_{out}$ is used as the input of the second noise cancellation module, and the actual channel matrix $\mathbf{H}$ is also set as the label, and the above operation is repeated to obtain the final channel estimation matrix $\hat{\mathbf{H}}_{DCNN}$ of DCNN. The above channel estimation can eliminate the noise interference and achieve better accuracy.

IV. SIMULATION RESULTS

In this section, we provide the simulation results of the DCNN based channel estimation scheme for vehicular OTFS communication system. The vehicle is regarded as a single antenna transmitter and the base station (BS) is set as the receiver with four received antennas. We adopt 3GPP standardized urban scenario channel modeling [4]. In the training process, the size of epoch is set to be 300, the learning rate is 0.0001, and the normalized mean square error (NMSE) is applied as the loss function in training to get the optimal model with the minimum loss. We compare the NMSE performance of the proposed DCNN method with OMP algorithm and the pilot-based scheme to demonstrate the superiority of the DCNN method.

40,000 samples are used for training the DCNN and the ratio of the training set to the validation set are set as 3:1. After the training of the DCNN method, 4,000 Monte Carlo simulations are performed at each SNR to verify the NMSE performance of the DCNN method. The specific simulation parameters of the DCNN method are shown in Table I.

The NMSE performance of the proposed DCNN method, OMP algorithm, and the pilot-based scheme is shown in Figure. 6. It is found that the DCNN method performs much better than OMP algorithm and the pilot-based scheme because the DCNN method is a nonlinear estimator that can learn the noise features

and eliminate the noise. In addition, the DCNN method outperforms the other two conventional schemes, especially in the case of low SNR since the DCNN method can realize better noise feature extraction and achieve the noise cancellation well when the noise interference is strong.

TABLE I. SIMULATION PARAMETERS.

Parameter	Value
No. of subcarrier	128
No. of OTFS symbols	8
Vehicle speed (km/h)	40, 60, 80, 100, 120
channel model	urban
Optimization function	Adam
Loss function	NMSE
Activation function	ReLU
Learning rate	0.0001
Size of epoch	300

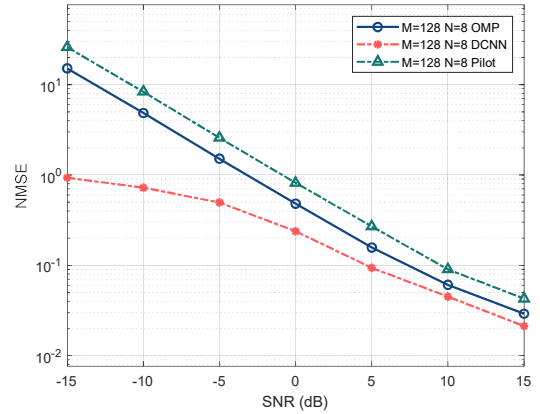


Figure 6. NMSE performance versus SNR (dB).

In the context of mobile vehicular communication, the channel parameters vary quickly with the increase of the vehicle speed. According to the characteristics of the DCNN method, it has good robustness to the variation of channel parameters. Figure. 7 shows the effect of vehicle speed on the NMSE performance at $SNR = 5$ dB, 10 dB and 15 dB. It is seen that the NMSE performance gradually decreases when SNR increases at

the same speed. When the SNR is fixed, the vehicle speed increases from 40 km/h to 120 km/h, but the NMSE performance is almost unchanged. This is because the DCNN method has a strong adaptability to the variable channel parameters. Therefore, the DCNN method proposed in this paper has good robustness under different vehicle speeds, which can realize the channel estimation with high accuracy even when the vehicle speed is changed and enhance the reliability of communication in the vehicular communication scenarios.

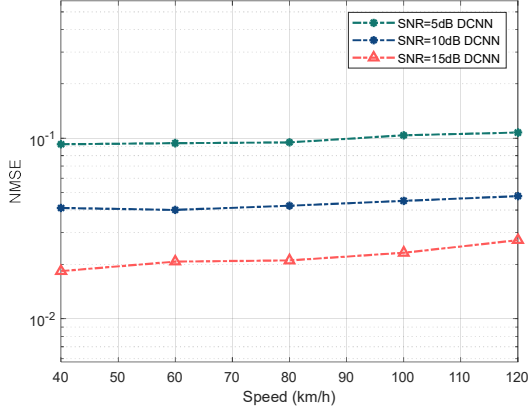


Figure 7. NMSE performance versus vehicle speed at different SNR.

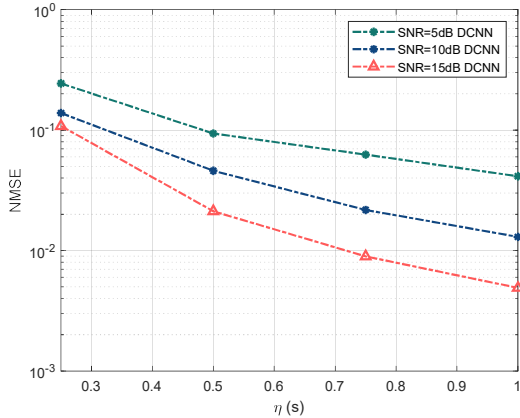


Figure 8. NMSE performance versus η at different SNR.

In OTFS communication system, the time delay affects the DD domain channel. Therefore, we consider the signal arrival time (η) from user to BS in vehicular communication scenarios. In the simulation, We set the vehicle speed to 80 km/h uniformly. Figure 8 depicts the effect of η on the NMSE performance at different SNR. It is found that the NMSE performance gradually improves when η increases at the same SNR. Since the higher delay can improve the delay resolution in the DD domain, thus making channel state characteristics better. Meanwhile, the NMSE performance of the DCNN method does not varies significantly when η changes from 0.25s to 1s, which proves that the DCNN method has good robustness under different η and has better channel estimation stability in different vehicular communication scenarios.

V. CONCLUSION

In this paper, a DCNN based channel estimation scheme for vehicular OTFS communication system is proposed. OMP algorithm is first employed for the fast pre-estimation. In addition, HDC and residual path are combined into CNN to extract the noise features and eliminate the noise influence, which further improves the accuracy of estimation. Simulation results demonstrate that the proposed DCNN method can achieve better performance under low SNR region compared with the other conventional channel estimation schemes and show good robustness to Doppler expansion under different vehicle speeds. Our future research may focus on the low complexity DCNN model design and optimization.

ACKNOWLEDGMENT

This work was supported in part by the Key Project of National Quality Infrastructure System of National Key Research and Development Plan under Grant 2022YFF0604900, in part by the Innovation and Development Joint Foundation of Shandong Provincial Natural Science Foundation under Grant ZR2021LZH003, in part by the National Natural Science Foundation of China under Grant 61771291, and in part by the National Research Foundation of Korea under Grant MSIT-NRF-2020R1A2B5B02002478.

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