Machine Learning-Assisted OFDM-Based DSRC Communication Systems

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***Abstract*—The automotive industry has developed Dedicated Short-Range Communication (DSRC) technology for specific Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication applications. However, the effectiveness of DSRC communication is highly dependent on other integrated standards for interoperability, which is still room for research, especially under high mobility. Deep learning has recently played a crucial role in boosting the system performance in 5G-and-beyond networks. This paper utilizes deep learning to improve the channel estimation quality of DSRC systems under time-variant and frequency-selective channels and applying a post filtering process to enhance the quality of reconstructed images. We consider an OFDM-based system where the propagation channels are roughly estimated at the receiver by a low-cost least squares method. Then, the channel estimation quality is enhanced by a data-driven approach exploiting supervised learning. Numerical results manifest the added benefits of deep learning for improving the channel estimation quality and boosting the Bit Error Ratio (BER) compared to the traditional estimation methods. Besides, a post-filter is necessary to remove artifacts and residual errors in recovered image data. Quantitatively, the support of deep learning improves the channel estimation quality by about 30%. At the same time, the post-filtering process enhances the reconstruction quality in terms of the Peak-Signal-to-Noise Ratio (PSNR) up to 4dB.**

***Index Terms*—DSRC technology, OFDM, channel estimation, deep learning, image data**

I. INTRODUCTION

Wireless communication networks have been successfully deployed in the Fifth Generation (5G) by eliminating the access boundary, enhancing spectral and energy efficiency, and providing high data rate and low latency limitations on connectivity worldwide [1, 2]. The achievements of 5G networks are in response to the proliferation of many different devices with data-hungry applications simultaneously accessing the networks at the same time and frequency resource. Many advanced technologies should be integrated into the network infrastructure to attain superior improvements in system performance. More details, for improving the transmission quality by only utilizing the linear detection/transmission techniques at the transceiver, massive Multiple-Input Multiple-Output (MIMO) has been approved its success in both academia and industry [3, 4]. In Massive MIMO communications, the randomness of the channel gains can be approximated by a deterministic mean value, thereby simplifying the signal processing and attaining the spectral efficiency close to the optimal in many scenarios. For short-range applications, the above-6GHz frequency range called mmWave communication has been suggested in, for example, [5, 6] and references therein. Thanks to the use of very high carrier frequencies, mmWave communication systems offer new stable facilities to acquire the high peak transmission rate with broadband radio links and dominant line-of-sight paths. Nonetheless, the challenging questions still remain as to how the mmWave technology could be utilized reliably for the applications of vehicular communications [7].

Intelligent Transport System (ITS) communication systems are parts of 5G-and-beyond networks with plenty of new technical and specific methodologies to efficiently guarantee the transport systems are secured and reliable [8, 9]. Dedicated Short-Range Communication (DSRC), known as IEEE 802.11p or WAVE, is a medium and/or short-range radio frequency communication technology designed, specifically for vehicle environments toward real-time, good data throughput, accurate, and reliable connectivity between vehicles and vehicles with high mobility [10]. DSRC can ensure the transmission rate and communication quality among the vehicles without any support from roadside infrastructure. The DSRC technology has been recommended to integrate into 5G new radio communications to increase performance safety [11]. Nevertheless, DSRC may not effectively meet the strict requirements of multimedia communication services, especially on detailed information preservation and high-resolution files, due to its limited coverage and capacity, and therefore still room for future study. In addition, as represented in [12], the traditional signal processing techniques may suffer from high costs to obtain the global solution; thus, they are only considered to evaluate the system performance in research and still cannot be implemented in practical systems for the time being.

Image and video are regularly used data in Vehicle-to-Vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. Large-size and detailed information contained in images and videos raises a vital issue that

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has attracted a lot of interest in upgrading the performance efficiency due to higher data throughput demands and increasing data resolution nowadays than before. In [13], the authors investigated the high-speed image sensors for V2V communications using visible light communication and demonstrated fundamental findings for a vehicle motion model and range estimation. Besides, quality of service-aware constraints reported in [14] allows various types of applications and new services ranging from road traffic safety, logistics, and infotainment. The system performance and quality of media transmission are multivariate functions of required data rate, latency, allocated bandwidth, and communication reliability. Besides, DSRC communication has utilized to send captured license place images to the server with real-time information acquisition [15]. We note that these previous works more focused on the application layer instead of studying the system performance in the vision of the physical layer with aspects of wireless environments.

Machine learning in general and deep learning, in particular, have recently attracted lots of attention in many different fields due to their flexibility and enhanced system performance. Deep learning can learn the system characteristics from a large amount of empirical data set and properly deploy it for performance optimization [16]. For the channel estimation, the authors in [17] manifested that a fully connected neural network could estimate the Rayleigh channels with lower normalized mean square errors than the blind method. Apart from this, the 5G-channel profiles based on the long-term evolution report in frequency-selective environments were effectively learned and predicted in [18]. For the flat-channel profiles, the power allocation can be predicted in sub-milliseconds by a deep neural network after sufficiently training to learn the features of the wireless networks under near-far effects patterns [19]. We notice that there is no related work investigating the applications of neural networks for Orthogonal Frequency-Division Multiplexing (OFDM)-based DSRC communication systems and then used it for evaluating the system performance.

To the best of our knowledge, it is the first time in the literature we have investigated the image data transmission over a DSRC environment and frequency-selective channels. Several approaches will be proposed to enhance the recovered data under high mobility. Our contributions are summarized as follows:

- We present an OFDM system for practical DSRC communication under wideband channels and the mobility of the transceiver. For practical aspects, the channel state information should be estimated at the receiver by gathering and processing the pilot signals in each OFDM symbol.
- We investigate a hybrid low-cost channel estimation technique, where roughly the least square estimation is first used to estimate the instantaneous channels roughly. Then, the data-driven approach is applied to boost the channel estimation quality by attracting more side information with supervised learning.
- We exploit unsupervised learning to mitigate residual errors and enrich the texture of media data via processing the spatial correlation among pixels.
- Numerical results demonstrate the benefits of using deep learning for channel estimation in DSRC communication systems. Besides, post-data processing improves the visualization of recovered image signals significantly.

The rest of this paper is organized as follows: Section II presents in detail the considered DSRC communication model comprising the network architecture, signal model, and propagation channels. The deep learning solution to improve the channel estimation quality is shown in Section III. Furthermore, Section IV describes a method to enhance the fine details of recovered images. The numerical results are given in Section V to validate the considered DSRC system. Finally, the main conclusions are drawn in Section VI.

II. DSRC Communication Model Under Frequency-Selective Channels

This section presents the DSRC communication model under the mobility and influence of frequency-selective fading channels.

A. *Preminary of DSRC Communications*

In this subsection, we focus on the DSRC communications adapted to the physical layer with one example as illustrated in Fig. 1 for the short-range communication between a transmitter and a receiver. DSRC communication technology allows a vehicle to communicate with other vehicles on the same road or other roads. In more detail, the carrier frequency is typically selected at 5.9 GHz with the bandwidth up to 75 MHz recommended by the European ENV standard [20] and demonstrates its effectiveness over short to medium propagation distances for many different types of applications. Under urban environments and none-line-of-sight (NLoS) communication links, the propagation distance that the DSRC technology can be deployed is up to 520 m, while it is up to 1219 m on expressways and about 1700 m inside tunnels [21].

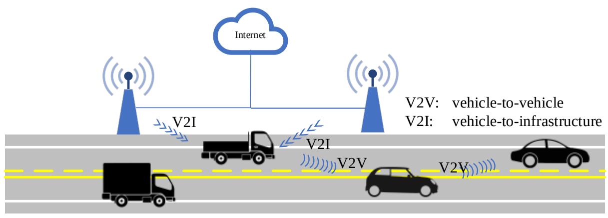

Fig. 1. The applications of DSRC technology in Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications.

As reported in [20], the DSRC technology may be deployed in both V2V, and V2I formats, relying on the basis of 5G cellular networks, as shown in Fig. 1. The transmitter and receiver communicate using a transponder called on-board units (OBUs) or roadside units (RSUs). In particular, a vehicle can transmit data to another through an OBU, establishing a V2V communication protocol. V2V communication is often used for safety purposes, for example, to notify the driver of one car that another car in front of it will slow down or nearly stop. In V2I communication, a vehicle equipped with an OBU may send data to the surrounding infrastructure, where an RSU is installed. The communication purposes are to alert the drivers of safety dangers, such as the car turning left or right at a crossroad or a curve too quickly. In addition, the V2I communication can be deployed for collecting tolls and parking payments. For such purposes, processing image data is of paramount importance, especially with low-resolution images.

B. *Impacts of Frequency Slective Channels on the DSRC Communication Systems*

Due to the movement of vehicles, the impacts of time-variant and frequency selective channels should be a crucial research direction in the wireless networks with the DSRC technology. In the time domain, the frequency selective channels appear as the length of symbols is smaller than the delay spread. In the frequency domain, it is equivalent to the phenomenon that the channel bandwidth is less than the signal bandwidth. The inter-symbol interference inherently exists in the DSRC systems under the frequency selective channels that result from the received signal involving multiple versions of the transmitted signal with different delays and attenuations.

In order to overcome the reduction of signal power over the frequency selective channels, the OFDM technology is adopted because of its robustness from the multicarrier modulation. The data at the transmitter are modulated by a finite set of constellation points, and then fed into multiple carriers, each having a sufficiently narrow bandwidth to against the deep fading channels. The OFDM technology takes advantage of the orthogonality frequency relation and spacing among subcarriers to enhance the spectrum efficiency. Besides, Inter Symbol Interference (ISI) and Inter Carrier Interference (ICI) can be degraded by deploying a guard interval based on the delay spread and the orthogonality relation. Consequently, the OFDM technology is preferable for the DSRC systems in both V2V and V2I communications. In this paper, we will investigate in detail how to design an OFDM system adapting to the Doppler effects by the movement of the cars with DSRC technology.

It is evident that the perfect channel state information yields the best signal detection at the receiver, and the system operates the most reliable according to the real-time movement of vehicles. However, propagation channels are unknown in advance for practical systems and should be estimated from the pilot signals. The channel estimation errors reduce the quality of the signal recovery with a certain Bit Error Ratio (BER). We notice that the channel uncertainty directly affects traffic safety, which acquires prompt and reliable signals. Consequently, a proper channel estimation method is highly required. While the Minimum Mean Square Error (MMSE) estimation method may be highly challenging to implement due to the non-stationary of the real propagation channels with an uncommon distribution, the linear MMSE estimation method is a suboptimal solution that is possible to implement in polynomial time. Unfortunately, this estimation is still costly for many applications, especially when the vehicles move at high speed and the propagation channels vary quickly since the channel statistics should be updated very often. The least-square estimation is indeed low computational complexity and easily implemented without any statistical information requirements. The only demerit is that the least square estimation method may offer much lower performance than the other estimations, especially at a low SNR regime. Consequently, some prior information on the instantaneous channels should be provided to improve the accuracy of the least square estimation method.

III. Transmission Model

This section presents the system, signal, and channel models used in DSRC communications as shown in Fig. 2. In our considered system model, we assume that the instantaneous channels are not available at the receiver, and therefore the channel estimation is needed to decode the transmitted signals.

A. *Transmitter*

The transmitter sends a bit stream to the receiver. In particular, bit data are mapped into the finite constellation points by utilizing, for example, (QAM) quadrature amplitude modulation. At time slot t, a modulated data vector is formulated as

$$s(t) = [s_1(t), s_2(t), \cdots, s_N(t)], \tag{1}$$

where $s_n(t)$ is the n-th constellation data symbol, and N is the number of modulated data symbols sent in this time slot.

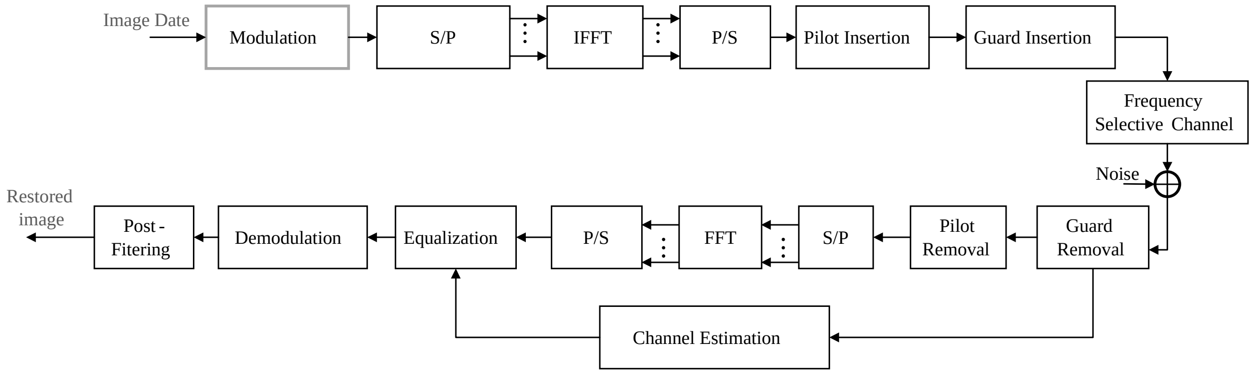

Fig. 2. The considered OFDM-based DSRC communication system over the frequency selective channels.

This modulated data vector will be transformed from the frequency domain to the time domain by using the Inverse Fast Fourier Transform (IFFT). Let us denote $\tilde{s}(t)$ the data signals in the time domain; then, it is formulated as follows

$$\tilde{s}(t) = \mathrm{IFFT}(s(t)). \tag{2}$$

After that, a cyclic prefix comprising N_G symbols is inserted into each OFDM symbol to mitigate the inter-symbol interference. Consequently, the transmitted data signal vector is denoted as $\tilde{s}(t)$ that includes $N_{\mathrm{IFFT}}+N_G$ symbols. In practical systems, image data should be passed through the source coding for compression due to their correlation and memory consumption. However, in the literature, many previous works have treated the source coding and modulating signals independently when considering the system performance of wireless networks over fading channels. Jointly compressing and modulating data are of interest for future work.

B. Channel Modelling

The channel model for communication systems using the DSRC technology is complicated due to the severity of randomness from the deep fading and high speed of vehicles in specific scenarios. Nonetheless, the channel impulse response is mathematically formulated as

$$h(\tau,t) = \frac{1}{\sqrt{LM}} \sum_{j=1}^{L} \sum_{m=1}^{M} c_j \exp(2\pi f_{jm} t + \theta_{jm}) \delta\left(\tau - \tau_j\right) \tag{3}$$

where L is the number of clusters and M is the number of paths in each cluster with the same time delay. The Doppler frequency and Doppler phase are formulated as

$$f_{jm} = f_{D\max} \sin(2\pi u_{jm}), \tag{4}$$

$$\theta_{jm} = 2\pi u_{jm}, \tag{5}$$

where u_{jm} is randomly distributed in the range [0,1] by a uniform distribution. In (3), c_j denotes the channel magnitude of the j-th cluster. The transmitted signal $\tilde{s}(t)$ is passed through the DSRC channel as

$$y(t) = h(\tau,t) \otimes \tilde{s}(t), \tag{6}$$

where $\otimes$ denotes the convolution operator. We emphasize that the considered transmission model in (6) captures the fundamental properties of wireless communication systems using the DSRC technology by selecting proper channel properties. Consequently, the detailed channel information setting will be presented in Section V.

C. Receiver

The image is first recovered at the receiver based on the received signals and pilot information. After that, the reconstruction quality of this image is improved by utilizing a post filter because of spatial correlation exploitation. The main methodology is illustrated in Fig. 3. In particular, at the receiver, the received signal is formulated as follows:

$$\tilde{y}(t) = y(t) + w(t), \tag{7}$$

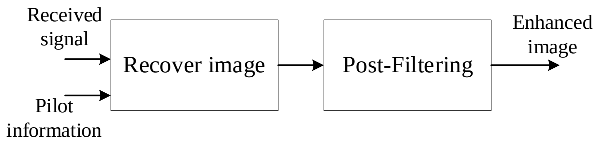

Fig. 3 The proposed receiver architecture comprising two main activities: Recover image based on the received signal and pilot information; Exploit a filter to remove noise and artifacts.

where $w(t)$ is the additive white Gaussian noise whose elements follow a circularly symmetric Gaussian noise with zero mean and standard derivation σ [dB]. From the received signal in (6), the cyclic prefix is first removed to obtain a signal of length N_{FFT}, denoted by $\hat{y}(t)$. The signal is then transformed from the time domain into the frequency domain by utilizing the FFT as

$$y_d(t) = \mathrm{FFT}(\hat{y}(t)). \tag{8}$$

Notice that from Eq. (7), the received pilot signal is precisely determined in the frequency domain for channel estimation purposes. The demodulation scheme further demodulates the signal to recover what the transmitter used. At this point, the output of the resulting OFDM-based DSRC system model is the final binary data sequence.

IV. Deep Learning-Assisted Channel Estimation

This section presents the feasibility of applying deep neural networks for DSRC communications. Besides, a fully connected neural network is constructed to enhance the channel estimation quality under the finite network dimensions.

A. Feasibility of Deep Neural Networks

This paper aims to design a neural network that can support the channel estimation module at the receiver. Due to the practical hardware, the additive noise at the receiver should be bounded in a compact set, i.e., each noise element should be bounded from below and from above. Moreover, one obtains that

$$0 \le \left\| h(\tau,t) \otimes \tilde{s}(t) \right\|_2 \le \left\| h(\tau,t) \right\|_1^{1/2} \left\| \tilde{s}(t) \right\|_2, \tag{9}$$

by utilizing the Holder inequality. The obtained result in Eq. (6) demonstrate that the received signals should be in a given finite range and our decoding process is align with the universal approximation theorem. Consequently, we can consider the channel estimation at the receiver as a continuous mapping and approximate it by a neural network with a finite number of neurons.

B. Neural Network Structure

We now construct a neural network from the above analysis to learn the time-variant channel impulse response applied to DSRC communication systems, which is illustrated in Fig. 4. In this paper, we focus on processing the image data, so CNN should be an excellent candidate to capture the channel properties. Even though CNN was originally used in image processing for restoration purposes, this neural network structure was confirmed to be potentially applied in wireless communications since the propagation channels creates correlations similar to image patterns [19], [22].

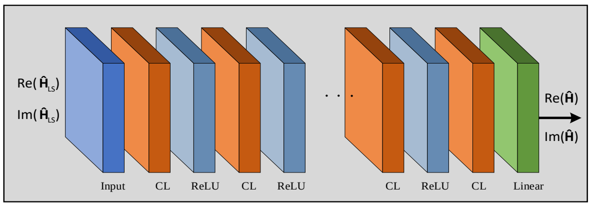

Fig. 4. The considered CNN architecture to learn and predict frequency-selective channels.

In addition, the weights and biases used for the CNN are usually small, leading to a low-cost design in optimizing the network parameters. The proposed channel estimation structure includes the two stages as follows:

- *Stage 1*: The raw channel estimates of the original channels are obtained by using least squares estimation.
- *Stage 2*: The channel estimates from the first stage are exploited to train a CNN that can predict a better channel estimation quality.

The received signal in Eq. (7) can be reformulated by the Hadamard product of the channel frequency response, and the transmitted signal as

$$y_d(t) = \tilde{h}(t) \odot \tilde{s}(t) + \tilde{w}(t), \tag{10}$$

where $\odot$ denotes the Hadamard product; and $\tilde{h}(t)$, $\tilde{s}(t)$, and $\tilde{w}(t)$ are the Fourier transform of the channels, signals, and noise. The MMSE estimation is an optimal estimator that produces the channel estimation error, but it requires the channel statistics, which are nontrivial to obtain for wideband channels under high mobility. In this paper, we use deep learning to support the least squares estimation since this method has low computational complexity and is suitable for fast fading channels without any prior information. Consequently, in the first stage, the channel estimate by using the least squares estimation is defined by using Eq. (8) as follows

$$\hat{h}_{LSd}(t) = \left(S(t)^H S(t)\right)^{-1} y_d(t), \tag{11}$$

where $(.)^H$ denotes the Hermitian transpose and the signal $s(t)$ is defined as

$$S(t) = \mathrm{diag}(\tilde{s}(t)), \tag{12}$$

where dig(x) creates a diagonal matrix from the input vector x such that its elements are on the diagonal. The channel estimates of all the subcarriers are further obtained by utilizing a linear interpolation method. We emphasize that the least squares estimation is widely deployed in practical systems due to its low cost as a consequence of no prior channel information. However, some useful channel statistics, such as the first and second moments, are not exploited, and therefore there is still room to improve the channel estimation quality. Specifically, the channel estimation errors are quite high for the communication systems using the DSRC technology under high mobility, e.g., cars have high speeds.

In the second stage, the considered CNN involves a two-dimensional (2D) input layer stacking the least squares channel estimates obtained from the first stage to produce the output comprising the better channel estimates. The output is obtained by a linear layer. Each group of the hidden layers consists of a convolutional layer and an activation layer. The complex channel estimates by the least squares estimation are split into real and imaginary parts and then reshaped into a matrix form before forwarding the input channel data into the convolutional layer. Mathematically, each convolutional layer z has a kernel of size $k_z{\times}k_z$ which convolutes with the input of this layer, denoted by I_z to obtain the output of this layer as follows

$$o_z = \mathrm{conv}(I_z, u_z) + b_z, \tag{13}$$

where u_z and b_z are the weights and biases of this convolutional layer, respectively. Besides, conv(·) is the convolution operator. In order for the considered CNN to imitate the nonlinear properties of the channel profile, the Rectified Linear Unit (ReLU) is utilized as an activation function, which is defined as

$$\mathrm{ReLU}(z) = \max(0, z), \tag{14}$$

where max(·,·) represents the maximum of the two values. Let us denote the channel estimates obtained by the least squares estimation as $\hat{h}_{LS}$, then it is divided into the real and imaginary parts as

$$I = \left\{\mathrm{Re}\{\hat{h}_{LS}\}, \mathrm{Im}\{\hat{h}_{LS}\}\right\}, \tag{15}$$

which characterizes the input dataset. Similarly, for the corresponding output, the dataset is defined as follows

$$O = \left\{\mathrm{Re}\{\hat{h}\}, \mathrm{Im}\{\hat{h}\}\right\}, \tag{16}$$

which includes the real and imaginary parts of the channel coefficients. The training phase handles the following continuous mapping

$$\left(\mathrm{Re}\{\hat{h}_{LS}\}, \mathrm{Im}\{\hat{h}_{LS}\}\right) \rightarrow \left(\mathrm{Re}\{\hat{h}\}, \mathrm{Im}\{\hat{h}\}\right), \tag{17}$$

which is so-called matrix mapping. In order to perform (15), the considered CNN minimizes the minimum mean square error (MMSE) between the channel estimates and the true channels as follows

$$L(U, B) = E\left\{\| \hat{h} - h \|^2\right\}, \tag{18}$$

where h is the actual channels that can be available during the training phase if one utilizes the sufficiently large transmit power to obtain very accurate channel estimates; $E\{\cdot\}$ denotes the expectation operator; ||·|| is the spectral norm; U and B are the sets containing all the weighted and biases. From the loss function in Eq. (16), the considered CNN can update the weights and biases via using the training dataset, which is numerically set up in Section VI.

V. Recovered Image Enhancement

The process presented in the previous section decodes the signals based on mitigating the fluctuations of random channels only. Alternatively, data structure, which provides various benefits, has not been considered yet. At the low SNR regime, the residual noise and artifacts still remain in the recovered image [23, 24]. We observe that the media data, such as images and videos, are highly related in the sense that there exists spatial correlation among neighbor pixels. The receiver can therefore exploit this prior information to enhance the recovered image quality both in the peak-signal-to-noise ratio (PSNR) and visualization, e.g., structural similarity (SSIM). We now define the recovered image from the previous steps as $\hat{X}$ that is formulated as

$$\hat{X} = \{\tilde{x}(t)\}, \tag{19}$$

where $\{\tilde{x}(t)\}$ are the collection of all the decoded signals over the data transmission. From (17), one post-filter will be deployed to smooth out the reconstructed image, therefore boosting the restoration quality. A post-filter for reconstructed images since there exists a correlation among pixels in a nature image and the signal processing procedures comprising OFDM and demodulation have not inherited the benefits.

The first post-filter utilized in this paper is Gaussian filter, whose kernel K of size $u \times u$ is defined as follows

$$K(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), \tag{20}$$

where each pixel of the image represents by a pair of the coordinates (x,y) with $-u \leq x \leq u$ and $-u \leq x \leq u$; $\exp(\cdot)$ is the exponential function. The Gaussian filter is popularly exploited in image processing due to its low cost and effectiveness in removing noise in high frequency components and blurred regions of the restored images. The enhanced image, denoted by $\tilde{X}$, is given as follows

$$\tilde{X} = \hat{X} \otimes K. \tag{21}$$

We stress that the Gaussian filter is popularly used in image restoration due to its low cost and flexibility in controlling the smooth level.

The second filter utilized in this paper is the Wiener filter. This is a minimum mean square (MSE) optimal linear filter, which enhances the image reconstruction quality by removing noise and reducing blurring effects. The parameter setting of the Wiener filter needs the assumptions of the second-order stationary on the noise and image signal processes. Specifically, the filtered image is formulated as

$$\tilde{X} = K_w \hat{X}, \tag{22}$$

where K_w is the Wiener filter that is defined based on the point-spread function, the power spectrum of signal and noise. Although the Wiener filter has low computational complexity, it is pretty slow to implement since it requires working on the frequency domain.

The third filter utilized in this paper is a dictionary learning algorithm called the K-SVD (singular value decomposition) filter, which exploits the patch-based model to create a dictionary for sparse presentation by utilizing the SVD on the noisy image [25]. Let us consider $\tilde{x}$ to be a patch of the original image, then the sparsest representation of the reconstructed image is formulated as follows

$$\min_{x} \|x\|_0 \quad \text{subject to} \quad \hat{x} \approx D\tilde{x}, \tag{23}$$

where $\hat{x}$ is the corresponding patch in the reconstructed image, and the dictionary D contains the atoms that define the similarities among the patches that are correlated to the current patch x. We notice that the K-SVD filter exploits the non-local similarity among pixels in an image to refine the reconstruction quality in our considered framework.

VI. Numerical Results

This section scrutinizes the system performance by utilizing different nature image data. The carrier frequency is 5.9 GHz, and the system bandwidth is 10 MHz. The modulation is QPSK (Quadrature Phase Shift Keying), and the number of FFT, i.e., the subcarriers, is 64. The number of subcarriers dedicated for the guard interval is 6. Consequently, the total number of subcarriers per OFDM symbol is 81. For the considered CNN, the training phase uses 100000 different realizations of the channel coefficients and those of the testing phase are 20000. In order to demonstrate the merits of the applications of deep learning to channel estimation in DSRC communications, the following benchmarks are used for comparison:

- Traditional least squares estimation (denoted as Least squares in the plots): The receiver simply deploys the least squares estimation method to estimate the propagation channels from the received pilot signals.
- Linear MMSE estimation (denoted as Linear MMSE in the plots): The receiver deploys the linear MMSE estimation method to estimate the propagation channels from the received pilot signals. This estimation method requires the covariance matrices of the channels and received pilot signals.
- Data-driven approach (denoted as data-driven in the plots): This benchmark is presented in Section IV with the supervised learning by using the channel estimates obtained by the least squares estimation method as the input.
- Perfect channels (denoted as Perfect CSI n the plots): This benchmark assumes that the fully instantaneous channels are available at the receiver.

In Fig. 5, we plot the BER as a function of the different SNR [dB] with the Doppler frequency of 30 Hz. The SNR level contributes an important role in improving the BER performance. In particular, the BER reduces significantly as the SNR increases observed by all the benchmarks. For example, in a network with an SNR of about 0 dB and perfect channel information, the BER is about 0.5. However, the BER reduces to 0.0025 as the SNR value is 14 dB. In addition, the least squares estimation method offers the worst BER among the considered scenarios without any prior channel information, while the linear MMSE estimation method gives better reliability than the baseline, especially at the high SNR regime, thanks to the effectiveness of exploiting the channel statistics. By gathering the channels to train the considered CNN, the data-driven approach yields superior improvements in the BER compared to the least squares estimation method, even outperforming the linear MMSE estimation method at the high SNR values.

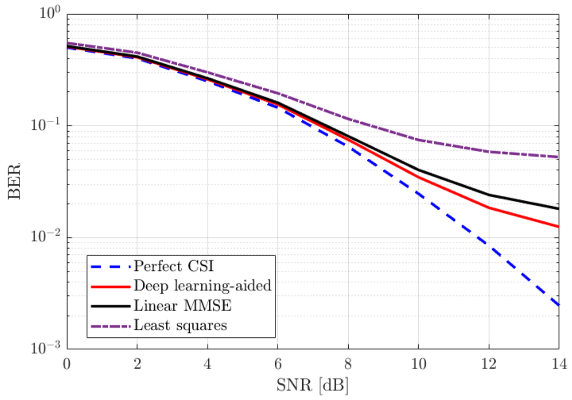

Fig. 5. BER versus the SNR [dB] with the Doppler frequency 30 Hz.

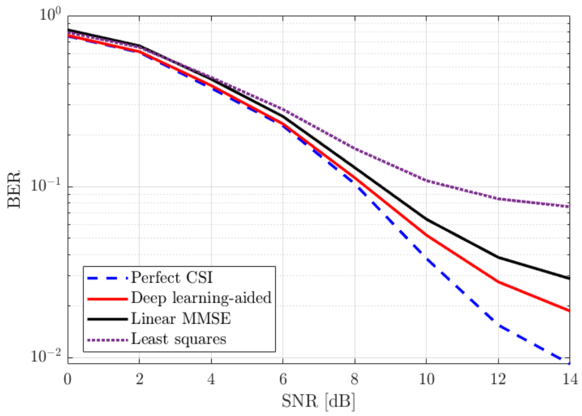

Fig. 6. BER versus the SNR [dB] with the Doppler frequency 50 Hz.

We plot the BER performance versus the different SNR values [dB] with the Doppler 50 Hz in Fig. 6. Due to faster movement, the BER is dramatically reduced at all the considered SNR settings. For instance, a network using the least squares estimation method and the SNR 12 dB reduces the reliability by about 45% as the Doppler frequency increases from 30 Hz to 50 Hz. Similarly, the BER performance of the data-driven approach, linear MMSE, and perfect channels reduces by 60%, 50%, and 53%, respectively. We note that the gap between the benchmarks becomes larger at the high SNR regime.

In Fig. 7, we show the image reconstruction quality by utilizing the different post filters as presented in Section V with the two natural images, Lenna and Parrot. For the sake of completeness, we also include the original images and the reconstructed images without post-filtering. One can observe that the reconstructed quality is very bad if only simply decoding image data from the received signals and the channel information. In particular, the peak signal-to-noise ratio (PSNR) is only about 15.96 [dB] and 16.71 [dB] for the Lenna image and Parrot image, respectively. By exploiting a post filter, the reconstruction quality is superiorly improved to the baseline. A Gaussian filter helps remove noise and artifacts from the reconstructed image and refine the image information with the PSNR values, i.e., 16.57 [dB] and 17.31 [dB] for the two considered images, Lenna and Parrot, respectively. A Wiener filter performs better than the Gaussian filter in our simulation settings, which gives the PSNR of 20.05 [dB] for the Lenna image and 25.52 [dB] for the Parrot image. Furthermore, the K-SVD filter offers a good reconstruction quality with the PSNR of 19.73 [dB] and 20.53 [dB] for the Lenna and Parrot images. In terms of the visualization quality, the K-SVD filter gives the best performance among the selected methods, thanks to the patch-based representation.

(a) Ground truth (b) Without filtering (c) Wiener filter (d) Gaussian filter (e) K-SVD filter

(g) Ground truth (h) Without filtering (k) Wiener filter (l) Gaussian filter (m) K-SVD filter

Fig. 7 The reconstructed image quality by various recovery schemes: (a) and (g) are the ground truths where (a) is Lennna image and (g) is Parrot image; (b) and (h) are reconstructed images without a post filter: (b) reconstructed Lenna image has PSNR = 15.96 [dB] and (h) reconstructed Parrot image has PSNR= 16.71 [dB]; (c) and (k) are reconstructed images with a Wiener filter: (c) reconstructed Lenna image has PSNR = 20.05 [dB] and (k) reconstructed Parrot image has PSNR= 20.52 [dB]; (d) and (l) are reconstructed images with a Gaussian filter: (d) reconstructed Lenna image has PSNR = 16.57 [dB] and (l) reconstructed Parrot image has PSNR= 17.31 [dB]; (e) and (m) are reconstructed images with a K-SVD filter: (e) reconstructed Lenna image has PSNR = 19.73 [dB] and (m) reconstructed Parrot image has PSNR= 20.53[dB].

VII. Conclusion

This paper has considered the time-variant channel estimation applied to DSRC communication systems. We have shown that the data-driven approaches can superiorly improve the channel estimation quality from the baseline by learning and predicting the channel features. Besides, we demonstrated that the reconstructed images from the received signal based on the channel state information still suffer from residual errors and artifacts. As one possible solution, the post-filtering process can mitigate such contamination and boost the image quality significantly. A potential extension for future work should consider the machine-assisted systems with the DSRC technology where the transceiver is equipped with multiple antennas.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Trinh Thi Huong proposed the idea and wrote the manuscript. Do Viet Ha performed simulation results and designed the CNN network. Trinh Van Chien proofread the paper and conducted the system model. All authors had approved the final version.

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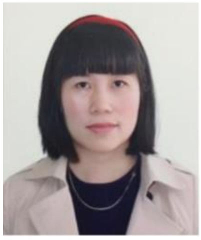

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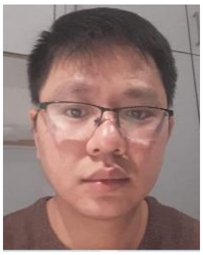

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