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Toward intelligent wireless communications: Deep learning - based physical layer technologies☆

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A B S T R A C T

Advanced technologies are required in future mobile wireless networks to support services with highly diverse requirements in terms of high data rate and reliability, low latency, and massive access. Deep Learning (DL), one of the most exciting developments in machine learning and big data, has recently shown great potential in the study of wireless communications. In this article, we provide a literature review on the applications of DL in the physical layer. First, we analyze the limitations of existing signal processing techniques in terms of model accuracy, global optimality, and computational scalability. Next, we provide a brief review of classical DL frameworks. Subsequently, we discuss recent DL-based physical layer technologies, including both DL-based signal processing modules and end-to-end systems. Deep neural networks are used to replace a single or several conventional functional modules, whereas the objective of the latter is to replace the entire transceiver structure. Lastly, we discuss the open issues and research directions of the DL-based physical layer in terms of model complexity, data quality, data representation, and algorithm reliability.

1. Introduction

Physical layer technologies are fundamental for the evolution of mobile wireless networks. In the Fifth Generation (5G) of mobile wireless networks, an Orthogonal Frequency Division Multiplexing (OFDM) -based air interface, referred to as the 5G new radio, is proposed to support services with highly diverse requirements, including enhanced mobile broadband services, the ultra-reliable low-latency communications, and massive communications [1]. In the physical layer, numerous novel technologies are introduced, including massive Multi-Input Multi-Output (MIMO), high-order modulation, and millimeter-wave communications.

Conventional signal processing technologies are confronted with various challenges caused by the high-order modulation, high carrier frequency, and a large number of antennas and subcarriers in 5G. In OFDM modulations, the high peak-to-average-power ratio is further aggravated owing to the large number of subcarriers and the high-order modulations of baseband signals [2], which may induce severe nonlinear distortions and low energy efficiency. In massive MIMO, the computational complexity of antenna selection and hybrid beamforming exponentially increases with the number of antennas, which may highly limit the scale of the antenna array and reduce the maximum cell data rate [3]. In a millimeter-wave transceiver design, the high carrier frequency and large bandwidth introduce severe hardware impairments, which are difficult to offset using existing radiofrequency components and baseband signal processing technologies [4].

To address such challenges, Deep Learning (DL) has recently been proposed as a novel data-driven signal processing technology [5,6]. DL can approximate arbitrary mathematical functions using Deep Neural Networks (DNNs), making it highly effective and efficient in solving complex and large-scale problems [7]. DNNs can serve as conventional signal processing modules or improve their performance by employing case-specific data information [8,9]. Moreover, they can replace the entire transceiver structure to achieve global optimization from an End-to-End (E2E) perspective [10].

In this article, we review DL-based physical layer technologies. In Section 2, we analyze the limitations of existing model-based technologies. In Section 3, we provide a brief introduction of classical DL architectures widely utilized in the physical layer. In Sections 4 and 5, we consider DL-based signal processing modules and DL-based E2E systems, respectively. DL-based signal processing modules use DNNs to replace or assist traditional signal processing modules, serving as an alternative

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solution or an auxiliary computational module to optimize a certain part of the physical layer. Alternatively, DL-based E2E systems use DNNs to replace the entire transmitter or the receiver, providing a novel DL-based E2E transceiver architecture to achieve global optimality. In Section 6, we discuss open issues and research directions in terms of model complexity, data quality, data representation, and algorithm reliability. In Section 7, we present the conclusions.

2. Limitations of conventional technologies

Although conventional signal processing technologies have achieved great success in practical communication networks, they still have several fundamental limitations as the physical layer becomes particularly complex in the 5G era.

2.1. Lack of model accuracy

Conventional signal processing technologies are based on rigorous mathematical models that are expected to precisely describe the physical layer details and their impacts on target signals. Thus, their performance is fundamentally determined by the accuracy of the corresponding mathematical models. However, acquiring a satisfactory model is becoming increasingly difficult as the system is becoming more complex [11]. Therefore, the performance of conventional physical layer modules can be highly degraded due to the lack of model accuracy.

For instance, low-cost but poor-performance radiofrequency components are used to reduce hardware costs in large-scale wireless communication systems, leading to severe nonlinear effects such as power amplifier nonlinearity, sampling frequency offset, and phase noise. Such hardware impairments are influenced by various factors, e.g., temperature, aging, frequency and individual differences, which are difficult to describe using precise mathematical models. Therefore, conventional modeling techniques may become unreliable, and the performance of the corresponding compensation techniques can be highly degraded.

DL-based methods can be used to process signal transmission issues with nonlinear effects when accurate models are unavailable because they show outstanding feature-extraction capability and can process raw data. Furthermore, DL provides an alternative modeling method for complex scenarios because it can implement approximating nonlinear functions with arbitrary accuracy as long as the network is sufficiently large. Thus, DL-based methods have been adopted in the physical layer to enhance certain parts of the conventional communication system.

2.2. Lack of global optimality

Conventional wireless communication systems consist of multiple functional modules [12], such as modulation and demodulation, channel coding and decoding, channel estimation, and signal detection. Such systems decompose the entire communication system into multiple functional modules, where each module focuses on an individual signal processing task. However, the objectives of such tasks can be highly divergent or even contradictory, making the decomposition generally lossy. Therefore, it is difficult for the conventional physical layer to achieve global optimality.

In OFDM systems, both high peak-to-average-power ratio reduction and signal modulation are essential functional modules of the transmitter [13]. The objective of the former module is to avoid the nonlinear region of the power amplifier by reducing the peak transmission power. Furthermore, the objective of the latter is to improve the modulation order to achieve a high data rate, which usually results in a high peak transmission power. In this case, these two modules can be optimized independently; however, global optimality is not achieved.

DL is considered a promising technology for implementing E2E transmissions, which can be used to achieve global optimality. A DL-based E2E system was proposed by adopting two DNNs to serve as the transmitter and receiver of the communication system [10]. The performance of this system was comparable to that of the conventional system in the additive white Gaussian noise channel.

2.3. Lack of computational scalability

Conventional signal processing algorithms are primarily based on mathematical optimization techniques, while their computational complexity can increase dramatically with the problem scale [14]. Therefore, the lack of computational scalability may become a critical issue that prohibits the application of conventional algorithms in large-scale networks.

Massive MIMO systems use a large antenna array to achieve high spectral and power efficiency and adopt antenna selection and hybrid beamforming to reduce hardware costs [15]. They only activate a subset of the antennas in each transmission, where the computational complexity exponentially increases with the antenna array scale. Thus, the conventional methods for optimizing antenna selection and hybrid beamforming are mathematically intractable in massive MIMO systems with hundreds of antennas.

DL also shows the ability to process high-volume data and sequence data because it can simply add extra modules to satisfy various requirements [16]. For example, convolutional layers are used to process numerous data issues, recurrent units are employed to acquire the correlation among sequence data, and pooling layers are used to decrease the number of dimensions. The flexibility of DL-based methods considerably alleviates the lack of computational scalability.

3. Deep Learning preliminary

DL resembles the information perception process in the brain to analyze and learn from the observed environmental data. DL has shown great success in solving large and complex classification problems, such as those related to pattern recognition, natural language processing, and image processing. This section provides a preliminary introduction of classical DL frameworks, which can be roughly categorized into deep supervised learning, deep unsupervised learning, and deep reinforcement learning.

3.1. Basic concept

The most fundamental architecture of DL is the DNN. It incorporates multiple hidden layers and computational neurons, thereby achieving highly improved representation capability. Each layer contains multiple neurons that are regarded as the basic computational unit. Each neuron performs an activation function, where the function exhibits various forms to match different objectives(Table 1).

The network training comprises forward and backward propagation phases. In the forward propagation phase, the loss between the network outputs and the data samples is calculated, where a loss function, such as cross-entropy, is usually utilized. In the backward propagation phase, the network parameters are tuned to minimize the overall loss using gradient descent algorithms, such as the stochastic gradient descent.

Table 1
Activation functions.

Name	$\sigma(u)$
Sigmoid	$\frac{1}{1+e^{-u}}$
Softmax	$\frac{e^{-u_n}}{\sum_m e^{-u_m}}$
Tanh	$tanh(u)$
ReLU	$\max(0, u)$
ELU	$\begin{cases} u, & \text{if } u>0, \\ a(e^u-1), & \text{otherwise.} \end{cases}$

3.2. Deep supervised learning

Supervised learning can train a DNN that maps input features to the corresponding label using labeled samples given beforehand [17]. The basic architecture in DNN supervised learning involves a Forward Neural Network (FNN). In FNNs, neuron connections only exist between adjacent layers. Owing to such a concise structure, FNNs are very attractive in feature selection, multilabel learning, and function approximation.

Other deep supervised learning models, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) also exhibit their advantages in various application fields, including text, audio and image processing. In RNNs, the neuron connections exist between adjacent layers as well as in neurons in the same layer, thus endowing it with context information exploitation capability. Thus, RNNs are widely utilized in natural language processing, such as speech recognition and machine translation. In CNNs, the convolutional layer is introduced, where a common convolution kernel is shared. The common kernel highly reduces the number of model parameters for high-dimensional inputs. Thus, CNNs are widely utilized in image processes, such as computer vision and image recognition.

3.3. Deep unsupervised learning

Unsupervised learning adopts unlabeled training samples and aims to determine the underlying patterns among its input features [18]. It saves extensive manual labor for labeling and is widely used in clustering, anomaly detection, and texture segmentation. Typical deep unsupervised learning models include the Autoencoder (AE), Generative Adversarial Network (GAN) and Deep Belief Network (DBN).

The AE consists of two DNNs: an encoder and a decoder. The encoder is used to compress the input features, while the decoder is used to reconstruct the original information. In AEs, problem-dependent constraints can be enforced by adding extra hidden layers between the encoder and the decoder. AEs are highly prevalent in image restoration, data denoising, and compression.

GANs also consist of DNNs, i.e., the generator and discriminator. The generator learns the implicit inter-relationship of input samples based on the feedback of the discriminator and finally acquires the objective distribution of the input samples. The discriminator learns to distinguish whether a sample is arriving from the generator or the real data set. The generator and discriminator attempt to fool each other during training, which is the so-called adversarial learning. The generator eventually learns to generate samples following the distribution of the input features. GANs are widely used in image generation.

DBNs comprise several stacked restricted Boltzmann machines. Each machine contains one visible layer and one hidden layer. For any two adjacent Boltzmann machines, the hidden layer of the former network serves as the visible layer of the latter one, which is called the shared layer. These networks can be trained in parallel using an unsupervised learning framework, thus highly decreasing the training complexity compared with classic DNNs. DBNs are widely utilized in automatic speech recognition.

3.4. Deep reinforcement learning

Reinforcement learning focuses on learning from the interaction between an agent and a complex environment, where the optimal actions are difficult to obtain [19]. A reward function is usually provided to evaluate the performance of action under an environmental state. The strategy is optimized during the interaction based on the feedback reward, which is expected to achieve a satisfying trade-off between exploration and exploitation. DNNs can be incorporated in reinforcement learning, i.e., deep reinforcement learning. In other words, the value function of the current state can be approximated using DNNs instead of traditional Q tables. Deep reinforcement learning inherits the advantages of both DL and reinforcement learning, making it a promising learning framework in the fields of simulation, gaming, optimization, and control.

4. DL-based signal processing modules

DL-based physical modules can improve the performance of certain modules using DL algorithms, which serve as alternatives to traditional algorithms. DL-based methods are model-free, and their performance relies on the characteristics of the transmitted signal itself instead of mathematical models in the conventional physical layers. Recent studies have employed this paradigm in numerous physical modules, such as modulation recognition, channel estimation, Channel State Information (CSI) feedback, signal detection, and channel decoding.

4.1. Modulation recognition

Modulation recognition is a key software-defined radio technology that enables cognitive users to recognize different transmission technologies to dynamically share the same spectrum without any system information. Conventional modulation recognition techniques can be classified into two categories, i.e., likelihood-based decision-theoretic methods and feature-based statistical pattern recognition methods. Likelihood-based methods use rigorous statistical assumptions with prior knowledge, which usually results in high computation complexity. Feature-based methods employ learning-based classifiers, such as artificial neural networks, random forest, multilayer perception, and support vector machines, which require a large amount of manual labor for feature extraction. In addition to high computational complexity and heavy manual work, conventional modulation recognition methods perform poorly in scenarios involving low Signal-to-Noise Ratios (SNRs) and high interference [20]. To overcome these drawbacks, various DL-based techniques have been introduced [21–23]. Compared with the conventional techniques, DL-based methods can avoid manual feature extraction and achieve highly improved accuracy and robust modulation recognition.

As shown in Fig. 1, DBN-based methods utilize a stacked neural network to extract features from the received signals and a conventional classifier to determine the corresponding modulation type. Each restricted Boltzmann machine can be trained separately; hence, the method can achieve lower complexity with fewer training parameters than other DL-based methods [21]. CNN-based methods (Fig. 2), treat the received signals as two-dimensional images in the I – Q space, amplitude – phase space or time – frequency space and use a CNN to classify the modulation type from a raw signal input. Additionally, multistep hierarchical CNN can be employed to further increase the classification accuracy by decomposing the modulation recognition problem into a series of subproblems, including CNN-based methods (Fig. 2) classification, modulation mode classification, and modulation order classification [22]. CNN-based methods achieve considerably improved performance in high SNR regions than other DL-based methods.

As shown in Fig. 3, Long – Short Term Memory (LSTM) -based

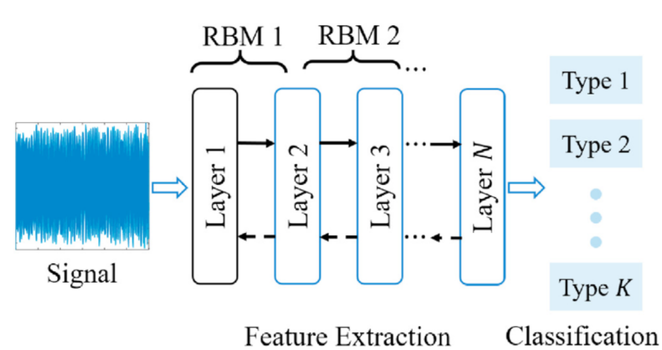

Fig. 1. Architecture of the DBN-based modulation recognition.

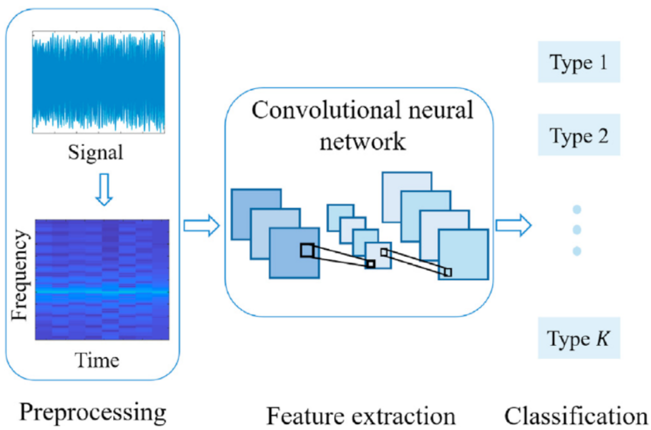

Fig. 2. Architecture of CNN-based modulation recognition.

methods simultaneously treat a sequence of signals in continuous time [23]. Owing to the recursive structure, temporal correlations between signals can be extracted to further improve the classification accuracy. Compared with other DL-based methods, LSTM-based methods can handle signals with variable lengths, providing more flexibility in practical implementation.

4.2. Channel estimation

Channel estimation is an essential part of the receiver design in modern wireless communication systems. Conventional channel estimation technologies can be classified into pilot-aided estimations (e.g., Least-Square (LS) estimation), which use predetermined pilot symbols to estimate the channel response, blind estimations (e.g., maximum likelihood estimation), which explore the statistical characteristics of the received signal with the prior knowledge of the channel order, and semiblind estimations (e.g., subspace-based estimation), which combine both pilot-aided and blind estimation techniques to achieve high accuracy with limited pilot symbols. However, pilot-aided methods are sensitive to the noise level and may introduce excessive overhead in the case of high mobility support and a large number of antennas. Blind methods require the prior knowledge of the channel and suffer from high computational complexity because of iterative matrix decompositions. To overcome these drawbacks, data-driven channel estimation methods that employ DL technologies have recently been proposed [24–26], which avoid inaccurate channel modeling observed in conventional methods by directly extracting channel information from the received data.

DNNs are introduced in pilot-aided estimation methods to reduce the required number of pilot symbols, which is regarded as the semiblind estimation method. As shown in Fig. 4, a conventional LS estimator is employed to generate the initial channel response estimation $\hat{\mathbf{H}}_t^{LS}$ using pilot information $\mathbf{s}_t$ and corresponding received signal $\mathbf{r}_t$. Then, $\hat{\mathbf{H}}_t^{LS}$, $\mathbf{s}_t$, $\mathbf{r}_t$, and the estimation from the previous time $\hat{\mathbf{H}}_{t-1}$ are fed to the fully connected DNN, which outputs the final estimation of the current channel response [24]. The network can be trained offline using simulated data and can highly reduce the online computational complexity compared to conventional semiblind channel estimation methods.

The CNN can be incorporated into the conventional iterative estimator based on the approximate message passing algorithm in massive MIMO systems [25], where it is used to improve the estimation accuracy with a small number of radio frequency chains. As shown in Fig. 5, the channel response is iteratively extracted using the received signal $\mathbf{r}$ and the estimation outputs $\mathbf{H}_{l-1}$ and $\mathbf{z}_{l-1}$ from the previous estimator, where $\mathbf{H}$ is the channel response and $\mathbf{z}$ is the noise vector. The estimator in each layer comprises a divergence estimator that generates Gaussian noise and a CNN-based denoising network that extracts channel information from noisy signals. CNN-based iterative methods can achieve improved estimation accuracy with highly reduced computational complexity.

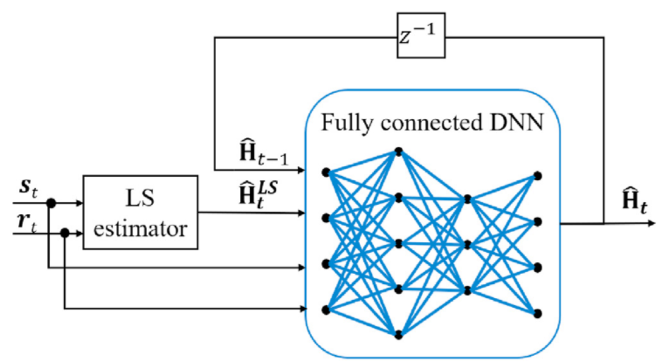

Fig. 4. DNN-assisted semiblind channel estimation.

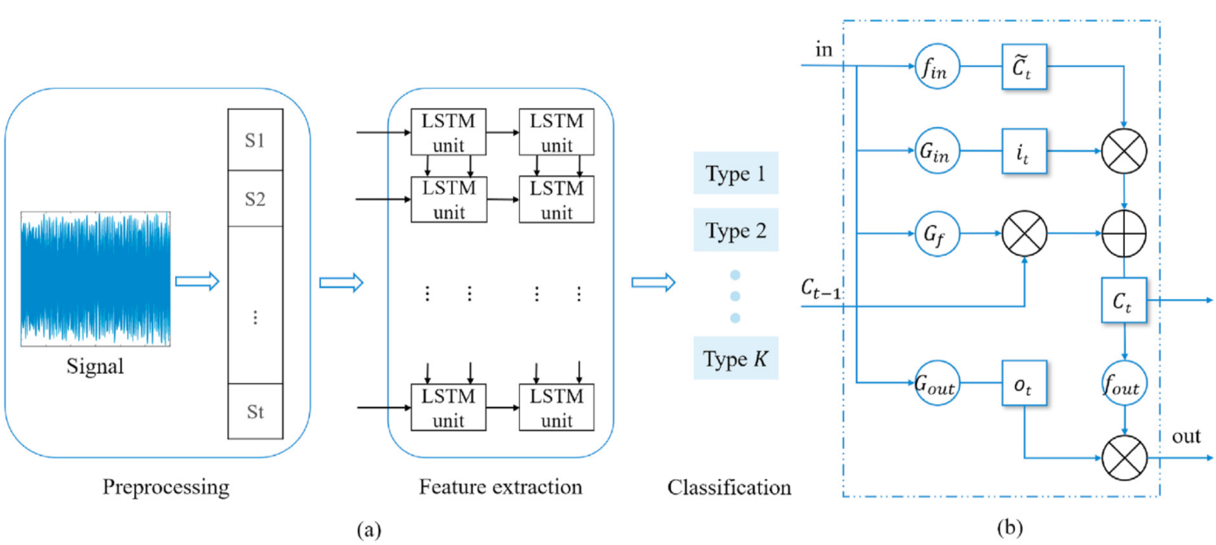

Fig. 3. Architecture of LSTM-based modulation recognition: (a)entire architecture; (b) structure of each LSTM unit, where C_t and C_{t-1} are the present and former memory contents, respectively; G_{in}, G_f, and G_out are the input, forget, and output gates with the sigmoid activation function, respectively; and f_{in} and f_{out} are the input and output tanh activation functions, respectively.

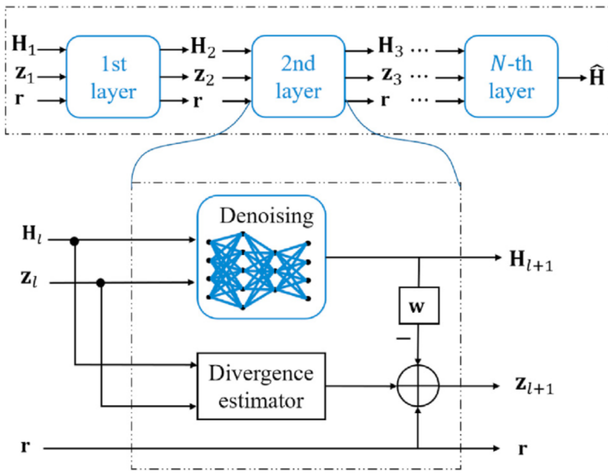

Fig. 5. Iterative estimator using CNN-based denoising networks.

4.3. Channel State Information feedback

The CSI feedback is critical for the success of multiantenna systems, where the system must feedback as much information as possible to the transmitter with limited signaling overhead. Recently, several DL-based CSI feedback methods have been proposed for massive MIMO systems using AEs [27–30]. Inspired by conventional compressive sensing methods, AE-based methods adopt a compression network as the encoder and a reconstruction network as the decoder(Fig. 6). During the training process, the encoder learns to compress the original CSI $\mathbf{H}$ into the compressed information $\mathbf{H}_C$ in a low-dimension space and the decoder learns to rebuild the channel from $\mathbf{H}_C$. If the reconstructed $\hat{\mathbf{H}}$ can approximate the original $\mathbf{H}$ with acceptable accuracy, we can transmit the compressed information in the feedback channel to reduce the signaling overhead.

The encoder usually employs a fully connected network to extract low-dimensional features from the original CSI, whereas the decoder may employ different hidden structures. For decoders, a CNN with a refinenet is a popular structure that can continuously refine the network to improve the reconstruction quality [28]. LTSM layers can also be incorporated to improve the performance in scenarios involving a low SNR and high compression ratio by extracting the time-varying features of the CSI [29]. Moreover, a residual network can be added to avoid gradient vanishing [30]. Compared with the AE-based method, the LSTM-based method reduces the normalized mean square error from 42% to 8% and from 54% to 10% for the indoor and outdoor scenarios of the COST 2100 channel model, respectively, while the runtime increases from 1 to 3 ms. DL-based methods can achieve higher compression ratios with higher reconstruction quality and faster convergency speed than conventional compressive sensing methods [31].

4.4. Signal detection

Signal detection is one of the most important functions in communications. It is used to recover original information from noisy signals. Optimal detectors (e.g., the maximum likelihood detector) can be derived using statistical models with known distributions. However, they usually suffer from a high computational complexity that is unacceptable for practical implementations; and thus, suboptimal detectors (e.g., various linear detectors) are usually employed to achieve a tradeoff between performance and complexity. In multicarrier and multiantenna systems, the difficulty of designing a high-performance signal detector increases considerably owing to the extended dimensions of the signal space, where suboptimal detectors based on approximate message passing and semidefinite relaxation detectors are widely investigated. However, these methods are highly sensitive to the accuracy of channel estimations and their computational complexity is unsatisfactory. To overcome these drawbacks, DL-based signal detectors have been proposed recently.

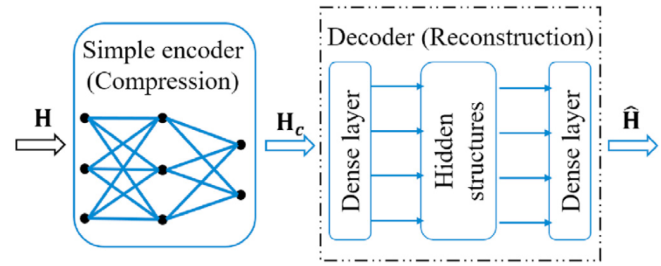

Fig. 6. AE-based CSI feedback.

A purely data-driven joint channel estimation and signal detection method is proposed in OFDM systems, where the received signal can be directly decoded using a fully connected DNN [8]. As shown in Fig. 7, the input of the DNN detector is the signal received after the fast Fourier transform, and the output is the recovered binary bits $\hat{\mathbf{s}}$. Note that the input signal comprises both data symbol $\mathbf{y}_D$ and the corresponding pilot symbols $\mathbf{y}_P$. The DNN-based method can achieve Bit Error Rate (BER) performance comparable to those achieved by the conventional LS and Minimum Mean Square Error (MMSE) methods. Moreover, it exhibits high robustness when the number of pilots and cyclic prefixes are reduced, or nonlinear distortions are introduced.

An improved model-assisted method is proposed, which combines an LS channel estimator and a Zero Forcing (ZF) signal detector with two DNNs, i.e., the channel estimation network and the signal detection network [32]. Compared with purely data-driven methods, model-assisted methods embed the prior knowledge of wireless communications, thus accelerating the convergence speed and decreasing the neural network scale. As shown in Fig. 8, the received symbols are first processed using the LS estimator and ZF detector to achieve conventional results $\hat{\mathbf{H}}_{LS}$ and $\hat{\mathbf{s}}_{ZF}$. Then, the results are fed into the DNNs as additional features to improve their performance. For the channel estimation network, the input is a conventional channel estimate $\hat{\mathbf{H}}_{LS}$, and the output is the recovered channel response $\hat{\mathbf{H}}$. For the signal detection network, the input comprises the predicted channel estimation $\hat{\mathbf{H}}$, received data symbols $\hat{\mathbf{Y}}_D$ and signal detection result of the ZF decoder $\hat{\mathbf{s}}_{ZF}$, while the output is the recovered binary sequence. This model-assisted method fully utilized domain knowledge, resulting in a faster convergence compared with the purely data-driven method. It is also shown that the proposed method can achieve a lower BER than the purely data-driven method and the conventional method with a linear MMSE estimator and an MMSE decoder.

DNN layers can also be embedded into a conventional iterative architecture to improve the detection accuracy or convergence speed. In Ref. [9], a DL-based detector was introduced to mimic the linear detector by unfolding the projected gradient descent algorithm as a neural network. As shown in Fig. 9, each hidden layer is regarded as one

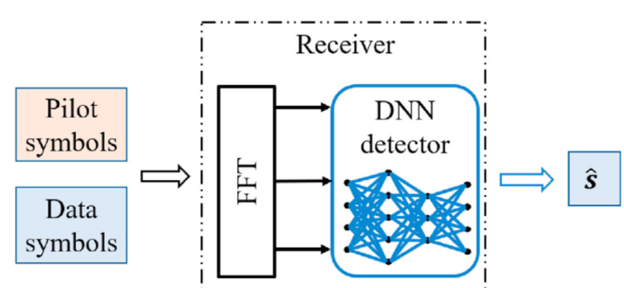

Fig. 7. Purely data-driven joint channel estimation and signal detection.

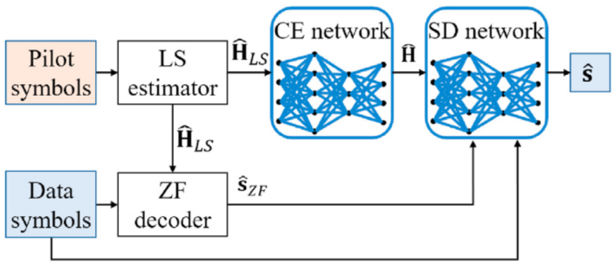

Fig. 8. Model-assisted joint channel estimation and signal detection.

iteration of the detection, where the input comprises the detection output of the former iteration, compressed received signal $\mathbf{y}$, and channel matrix $\hat{\mathbf{H}}$. This detector could achieve BER performance comparable to those achieved by approximate message passing and semidefinite relaxation detectors, with a faster convergence speed. Additional neural layers can also be introduced to further improve the performance of other iterative architectures, e.g., conjugated gradient descent detectors [33], message passing detectors [34], and orthogonal approximate message passing detectors [35].

4.5. Channel decoding

Channel coding is regarded as the most effective method for overcoming the imperfections of wireless channels, including noise, interference, and fading. The widely utilized channel coding techniques, such as the turbo code and low-density parity-check code, usually correspond to a complex iterative decoder. Neural network-based decoders have recently been proposed to achieve a better trade-off between decoding performance and computational complexity.

A DNN can be used as a decoder to directly recover the originally transmitted bits from noisy codewords [36]. The decoder adopts a fully connected DNN, of which the input is the received noisy codewords $\mathbf{y}$ and the output is the corresponding information bits $\hat{\mathbf{s}}$. Compared with conventional iterative decoders, the DNN-based decoder estimates the information bits through the hidden layers in one shot, which can highly decrease the decoding latency. The DNN-based decoder can achieve performance comparable to that achieved by the maximum a posteriori algorithm for the decoding of random codes and polar codes. However, the network scale and training complexity exponentially increase with the length of codewords. To extend the method with a large codeword length, a DNN-based partitioning method has been proposed, where multiple DNNs are introduced to decode multiple subblocks in parallel [37].

DL can also be utilized to decode hybrid codes in 5G scenarios, where three neural networks based on the DNN, CNN, and LSTM are proposed to simultaneously decode the polar codes and low-density parity-check codes [38]. These three decoders share the same unified structure, in which the input comprises the received symbols and an indicator section that defines the code type, while the output comprises the estimated information bits. These three DL-based methods exhibit competitive BER performance compared with the conventional belief propagation (BP) decoder, with a significant throughput improvement.

DNNs can also be incorporated as auxiliary functional blocks to improve the performance of conventional decoders. Fig. 10 illustrates a CNN-assisted BP decoder, where a CNN-based denoiser is incorporated into a conventional BP decoder [39]. A CNN is used to approximate noise $\mathbf{n}$, which helps improve the reconstruction quality of the original codeword $\mathbf{x}$ from the noisy codeword $\mathbf{y}$. For the CNN denoiser, the input is the estimated noise $\tilde{\mathbf{n}}$ and the output is the corrected noise $\hat{\mathbf{n}}$. For the BP decoder, the input is the denoised codeword $\mathbf{y}_d$ and the output is the estimated codeword $\mathbf{x}_d$. The CNN-assisted BP decoder iteratively processes the received symbols between the BP decoder and CNN-based denoiser, thereby exhibiting considerable BER performance improvement in low SNR regions compared with the conventional BP decoder. To address time-varying channels, RNN-assisted conventional decoders are investigated, including the RNN-assisted BP decoder and random redundant iterative decoder, further improving the error correction accuracy [40].

5. DL-based end-to-end system

Although DL-based signal processing methods improve the module performance, they cannot achieve global optimality. Thus, the DL-based physical layer must be reconsidered from an E2E perspective, in which an integral AE structure can be utilized to replace the individual function blocks.

In the AE structure, the entire transmitter is replaced by a single DNN, referred to as the encoder, where the input is the original bit information and the output is the transmitted signal. The receiver is also replaced by a DNN, referred to as the decoder, where the input is the received signal and the output is the reconstructed bits. The encoder and decoder networks are jointly trained by minimizing the loss between the original and reconstructed information. Furthermore, GANs and retraining techniques can be introduced to address the difficulty of the gradient backpropagation of practical wireless channels.

5.1. Basic AE-based method

In the basic AE-based method (Fig. 11) the original message $\boldsymbol{s}$ is encoded as a one-hot vector, which consists of "0"s in all dimensions, with the exception of a single "1" in a dimension used uniquely to identify $\boldsymbol{s}$. The encoded message is then fed into the encoder network, where the parameters of the last layer are fixed to reflect certain hardware constraints, such as the energy constraint, and outputs the transmitted signal $\boldsymbol{x}$. The decoder takes the baseband received signal $\boldsymbol{y}$ as its input and reconstructs the one-hot message, which is then decoded to recover the estimated message $\hat{s}$. The AE-based transceiver can learn modulation methods similar to conventional systems and achieve comparable Block-Error-Rate (BLER) performance [10].

The basic AE-based method can be extended by incorporating the LSTM and CNN into the architecture to compress the original message in

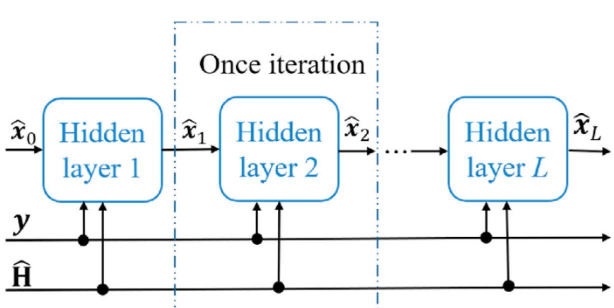

Fig. 9. DL-based unfolded iterative detection.

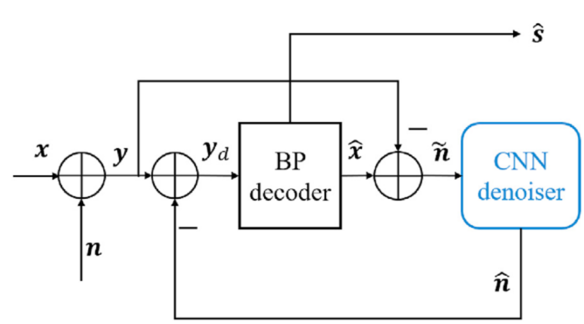

Fig. 10. CNN-assisted BP decoder.

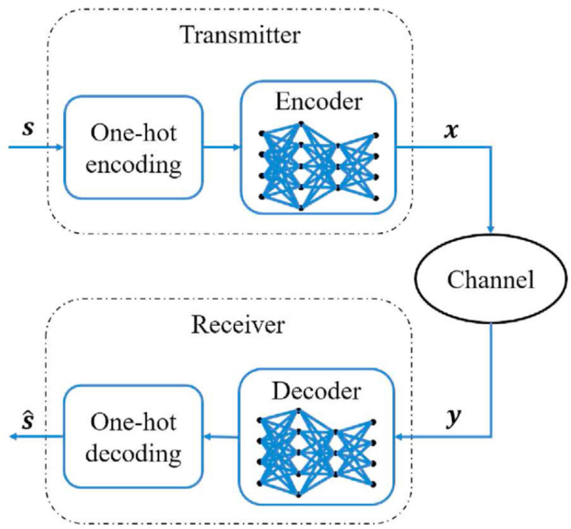

Fig. 11. Basic AE-based E2E systems.

text and image transmission, respectively, where BER performance can be further improved [41,42]. It can also be extended to MIMO systems by expanding the dimensions of the encoder output and the decoder input according to the number of transmitting and receiving antennas [43]. The AE-based method achieves a lower symbol error rate than the classic MIMO schemes when the signal-to-interference-plus-noise-ratio exceeds 16 dB.

5.2. GAN-assisted method

In the basic AE-based method, the wireless channel is usually described using a statistical model, e.g., Rayleigh fading channels, such that the gradient backpropagation is available for the joint training of the encoder and decoder networks. However, the wireless channel can be highly complex in practical networks, and geometry-based stochastic models are widely used to accurately describe the behavior. In such models, the gradient backpropagation is not feasible for the derivative of channel transfer functions, blocking the joint training of the encoder and decoder networks.

One way of addressing the block of the gradient backpropagation issue is to simulate the gradient over a derivable approximated channel, where the conditional GAN-based method is proposed to approximate the complex real channel model [44]. A conditional GAN is illustrated in Fig. 12, where the generator takes the transmitted signal $\boldsymbol{x}$ as the input under the condition of the received pilot signal $\boldsymbol{y}_p$ and outputs a received signal $\boldsymbol{y}$ and the discriminator takes the received signal $\boldsymbol{y}$ as the input under the condition of $\boldsymbol{y}_p$ and outputs an assessment on whether the input is from the generator (fake) or the real channel (real). The generator and discriminator are jointly trained, such that the generator can learn the distribution of the real channel output and the discriminator can hardly distinguish between real and fake inputs. The GAN-assisted method outperforms conventional OFDM systems in terms of BER and BLER performances under the WINNER II channel.

5.3. Two-phase method

Another way of addressing the block issue is to avoid the gradient computing using the two-phase method, where the network can be retrained using data from real channel transmissions after the original transceiver is trained using analytical channel models or after the supervised learning framework is replaced by a reinforcement learning framework during the transmitter training. Note that the gradient backpropagation is not available for real channel transmissions; thus, the second training phase is applied separately only in the receiver part.

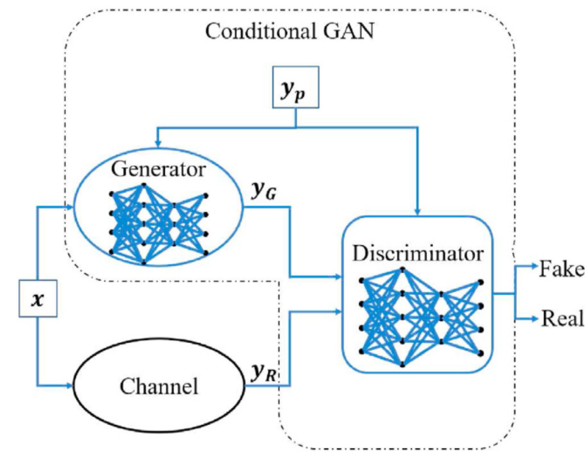

Fig. 12. GAN-assisted channel modeling.

In [45], the receiver was retrained using a supervised learning framework, where the input feature is the received signal $\boldsymbol{y}$ and the label is the original transmitted message $\boldsymbol{s}$. The retrained system outperformed the basic AE-based system, where the transmitted gain can be reduced by 1 dB at a BLER of 10^{-4}.

In [46], the traditional IFFT, FFT, and CP-related functions were reserved in the transmitter and receiver parts to extend the AE-based E2E system into multi-carrier systems. Note that multiple encoders (decoders) were deployed in parallel in the transmitter (receiver) for different sub-carriers. The same two-phase training was adopted as that used in Ref. [45]. The multicarrier system achieved performance comparable to that achieved by the conventional OFDM system with a QPSK modulator and an MMSE equalizer.

In [47], the receiver was trained using a supervised learning framework in the first phase. Further, the transmitter was trained using an RL framework in the second phase, where the original transmitted message $\boldsymbol{s}$ is regarded as the state, the transmitted signal $\boldsymbol{x}$ is the action, and the difference between $\boldsymbol{s}$ and $\hat{s}$ is the corresponding reward of the current transmission. By iteratively performing these two phases, it is shown that the RL training method converged faster and achieved BER performance comparable to that achieved by the basic AE-based E2E system.

6. Challenges of DL-based methods

Despite the potential benefits of introducing DL technologies in the design of wireless transceivers, many related challenges still require further studies. We discuss four major challenges, i.e., model complexity, data quality, data representation, and algorithm reliability.

6.1. Model complexity

The high computational complexity of DNNs results from the massive operations of floating-point multiplication and nonlinear activation functions in neurons. Massive operations can lead to high computational latency, which may not be an issue in conventional machine learning application fields but are fatal in wireless communications. In fact, the physical layer of mobile terminals does not allow online operations of large neural networks with millisecond delays. For example, DNNs must run within a latency of fewer than 12.5 μs to avoid buffer overflow for a data transmission rate of 80 MB/s and a buffer size of 1 kB [48].

Moreover, existing studies rarely consider hardware implementation issues, which may highly restrict the practical deployment of DL-based physical layer technologies. DNNs usually require tens of thousands of computation units, which are unavailable in current mobile terminals. Recently, some studies have shed light on the binarization method for the backpropagation algorithm, which requires fewer hardware resources than classical neural networks in practical systems [49].

Furthermore, the curse of dimensionality seems to be severe in the field of wireless communications. For instance, DL-based decoding methods must solve a multiclassification problem, where the number of classes exponentially increases with the code block length. In particular, the one-hot representation of a k-bit information block has 2^k dimensions, where k is commonly $10^3 - 10^4$ in typical wireless communication systems. Current solutions usually decompose the network into parallel smaller neural networks to reduce the dimension, which may degrade the overall performance. Thus, the curse of dimensionality can be a fatal defect in DL-based physical layer technologies.

6.2. Data quality

The performance of DL techniques highly relies on the quality of training samples, considering both diversity and validity. The lack of diversity may lead to underfitting, while invalid training data may result in model corruption. Most existing studies have generated training samples via model-based simulation platforms, where the authenticity of data is limited owing to the gap between the simulation platform and the actual propagation environment. Therefore, reliable data generation methods and real data from practical systems are highly required to promote the development of DL-based physical layer technologies.

6.3. Data representation

Data representation has a great impact on the performance of DNNs. For instance, there are two major representations in natural language processing, where the discrete representation (such as the bag of words and TF-IDF) is simple for implementation and the distributed representation (such as the n-gram, Word2Vec, and GloVe) considers statistical features and context correlations. However, existing DL-based work in the physical layer has neglected the importance of data representation, where I/Q vectors or amplitude/phase vectors are generally utilized. Such natural representations are designed for convenient communication systems, which may not be optimal for DL-based technologies.

The one-hot vector is considered in the AE-based E2E system, and it simplifies the data representation on both the input and output tensors [10]. However, the input dimension exponentially increases with the length of transmitted messages, leading to high model complexity, as discussed. Therefore, more concise and efficient data representations are required.

6.4. Algorithm reliability

The conventional physical layer adopts physical-based mathematical models to guarantee system reliability, where we can derive the upper and lower bounds of the system performance with corresponding mathematical formulas. However, DNNs are usually treated as a black box, leading to a lack of interpretability and may suffer from unexpected failures. Therefore, the implementation of DL-based methods in the physical layer might be unreliable.

To alleviate such issues, model-assisted DL methods have been proposed, where expert domain knowledge is embedded into the DNNs to initialize the network or guide network training [50]. For instance, the model-assisted joint channel estimation and signal detection method in Ref. [32] reduces the required SNR by 1 dB at BER $= 10^{-3}$ and saves almost 87% memory usage compared with the purely data-driven method in Ref. [8]. It also introduces a deep unfolding method to utilize DNNs as computational assistance to accelerate the convergence of conventional iterative algorithms. Model-assisted DL methods in the physical layer combine DL technologies with conventional model-based algorithms, thus enhancing the interpretability and improving the system performance in terms of convergence and reliability.

7. Conclusions

In this article, we present a literature review on DL-based physical layer technologies for 5G wireless networks. First, we show the limitations of conventional model-based methods in terms of model accuracy, global optimality, and computational scalability. Then, the existing DL-based physical layer technologies are categorized into DL-based signal processing modules and DL-based E2E systems, which are used to serve as alternative solutions for the existing functional modules and replace the entire transceiver structure to achieve global optimality, respectively. The DL-based solutions can compete with classic solutions in most scenarios and outperform the classic ones in extreme settings with unfavorable conditions. However, several technical challenges for the DL-based physical layer still exist, and further efforts are required to address model complexity, data quality, data representation, and algorithm reliability.

Declaration of competing interest

There is no conflict of interest.

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