Massive MIMO Channel Estimation for Vehicular Communications: a Deep Learning Based Approach

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***Abstract*—The estimation of the massive multiple input multiple output (MIMO) channel for vehicular communications is very challenging due to the variation of the channel and the requirement of low latency. To improve the accuracy and reduce the delay of the massive MIMO channel estimation, the recently emerging and popular deep neural network is exploited in this paper to learn the sparse structural information of the MIMO channel and estimate the channel more accurately and more rapidly. Firstly, a novel deep learning based massive MIMO channel estimation (DLCE) scheme is proposed, which achieves an efficient trade-off between the accuracy and the delay in channel estimation. Furthermore, exploiting the spatial correlation of the multiple antennas channel, an enhanced scheme called spatial-correlated DLCE (SC-DLCE) is proposed to further improve the channel estimation accuracy, especially in low signal-to-noise ratio environment. Simulation results demonstrate that the two proposed schemes can significantly improve the accuracy of massive MIMO channel estimation with a much shorter processing delay in practical vehicular communications terminals compared with the state-of-the-art benchmark schemes.**

***Index Terms*—vehicular communications, massive MIMO, channel estimation, deep learning, sparse recovery.**

I. Introduction

Vehicular communication is regarded as a dominant area of ultra-reliable low latency communications (URLLC) scenarios in the 5G wireless communications [1]. With the rapid development of the internet of vehicles, the channel estimation scheme with higher accuracy and lower delay is a popular research direction for vehicular communications and particularly V2X communications [2]. The techniques of orthogonal frequency division multiplexing (OFDM) and multiple input multiple output (MIMO) have gained great popularity from both academia and industry due to the anti multipath fading capability and high spectral efficiency. Combining their advantages, MIMO-OFDM has been widely adopted in the latest and next-generation wireless communication systems [3], [4].

In URLLC scenarios, the major challenge of practical MIMO-OFDM systems is to achieve reliable and realtime channel estimation. As reported in literature, the conventional channel estimation methods for MIMO-OFDM systems are often based on the training sequences (TS), i.e. the preamble in the time domain or the pilots in the frequency domain [5], [6]. However, a major drawback is that, the overhead of the required length of the training sequences will drastically increase when the number of multiple antennas is large, which will significantly reduce the spectral efficiency.

To solve this problem, the compressed sensing (CS) theory, which is a recently emerging sparse signal processing technique, is introduced to MIMO channel estimation to reduce the time and frequency training resource overhead and improve the spectral efficiency [7]. Previous research has proven that the CS methods can improve the estimation performance by utilizing the sparsity structure of the MIMO channels [8], [9]. Nevertheless, the classical CS algorithms still cost high computational complexity and limited recovery accuracy at low signal-to-noise ratio (SNR), especially for the V2X communication scenario which requires low latency. Although the structured CS methods exploit the structural sparse correlation of multiple channel measurements from a certain domain to further improve the sparse recovery accuracy [10]–[12], the processing delay and a large number of iterations are still the bottlenecks for CS-based methods. How to achieve a good trade-off between the estimation accuracy and the delay of vehicular communications channels has not been sufficiently addressed in literature yet.

Recently, the popular emerging deep learning techniques have been utilized to deal with the sparse recovery problems. By unfolding the iterations of the iterative shrinkage thresholding algorithm (ISTA) [13] and the approximate message passing (AMP) algorithm [14], the learned ISTA (LISTA) [15] and learned AMP (LAMP) [16] have been proposed to solve the convex sparse optimization problem in the framework of deep learning. Although the state-of-the-art conventional iterative algorithms of AMP and ISTA both utilize the structural sparse prior of the signal and employ recursive method to converge to sparse solutions, the delay caused by the repeated iterations is still preventing them from being applied in delay-sensitive vehicular communications. Compared with the conventional iterative methods, the deep learning based algorithms utilizing the neural networks can significantly reduce the processing delay.

In order to solve the problems of the existing iterative and CS-based sparse recovery methods, in this paper, the deep learning (DL) theory [17] and neural networks are exploited in the estimation of massive MIMO channels and two DL-based massive MIMO channel estimation schemes for vehicular communications are proposed, which are aimed to reduce the

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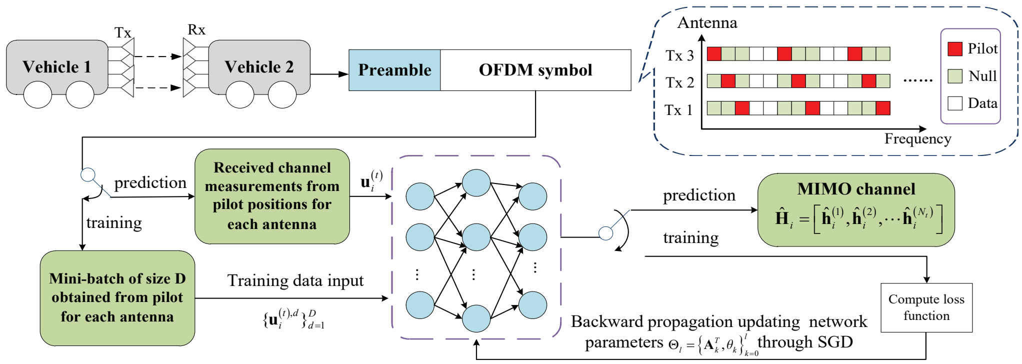

Fig. 1. The signal model of the massive MIMO-OFDM based vehicular communications system and deep learning based channel estimation.

delay and improve the accuracy of channel estimation. The contribution of this paper is summarized twofold as follows.

- A DL-based MIMO channel estimation (DLCE) scheme is proposed. The channel impulse response (CIR) of the MIMO channel, which is sparse in the tap delay domain, is acquired through the feed-forward calculation in the well-trained LAMP neural network with a series of network learnt parameters.
- To further improve the channel estimation accuracy, especially with low SNR, an enhanced neural networks based scheme called spatially correlated DLCE (SC-DLCE) is proposed. Making use of the spatial correlation of the sparse support structures of the channel CIR between different antennas, the desired sparse support of the MIMO channels is more efficiently learnt and predicted, both in the training and estimation phases.

Notation. Matrices and column vectors are denoted by boldface letters; frequency-domain and time-domain vectors are denoted by boldface vectors with tilde $\tilde{\mathbf{v}}$ and without tilde $\mathbf{v}$, respectively; $(\cdot)^\dagger$, $(\cdot)^T$ and $(\cdot)^H$ denote the pseudo-inversion, transpose and conjugate transpose operations, respectively; Π^c denotes the complementary set of the set Π; $\mathbf{A}_\Pi$ represents the sub-matrix comprised of the columns of the matrix $\mathbf{A}$ indexed by the set Π; $\max\{\mathbf{v}, S\}$ is an operator that returns the set composed of the indices of the largest S entries of the vector $\mathbf{v}$.

II. System Model

Considering the massive MIMO enabled vehicular communications scenario as illustrated in Fig. 1, a $N_t \times N_r$ MIMO transmission system with N_t transmit and N_r receive antennas is utilized. The L-length CIR associated with the t-th transmit antenna and a certain receive antenna during the i-th symbol can be modeled as

$$\mathbf{h}_i^{(t)} = \left[h_{i,1}^{(t)}, h_{i,2}^{(t)}, \cdots, h_{i,L}^{(t)}\right]^T \tag{1}$$

Without loss of generality, the method of channel estimation for each receive antenna is identical, so the receive antenna index is omitted in the CIR given by (1) and also in the following content, expect for explicitly stated otherwise. As illustrated in Fig. 1, the i-th time-frequency training OFDM signal structure of the t-th transmit antenna [10], with time domain training sequences in the preamble and frequency domain pilots, is composed of an M-length preamble $\mathbf{c} = [c_1, c_2, ..., c_M]^T$ and an N-length OFDM symbol $\mathbf{x}_i$ given by

$$\mathbf{x}_i = \left[x_{i,1}^{(t)}, x_{i,2}^{(t)}, ..., x_{i,N}^{(t)}\right]^T = \mathbf{F}^H \tilde{\mathbf{x}}_i^{(t)} \tag{2}$$

where $\mathbf{F}$ is the $N \times N$ discrete Fourier transform (DFT) matrix and N is the number of OFDM sub-carriers. All transmit antennas share the same time-domain preamble. The frequency-domain OFDM symbol $\tilde{\mathbf{x}}_i^{(t)} \in \mathbb{C}^N$ contains a small number of N_p pilots on the sub-carrier location set given by

$$D^{(t)} = \{d_n^{(t)}\}_{n=1}^{N_\mathrm{p}} \tag{3}$$

where $d_n^{(t)}$ is an index integer from 0 to $N-1$ denoting a pilot location. The pilots of different transmit antennas are distributed in the sub-carriers in an orthogonal pattern as illustrated in Fig. 1.

After cyclicity reconstruction implemented by extending the overlap-and-adding operation (OLA) [18] to retrieve the time-domain cyclic convolution between the transmitted signal and the channel CIR, the received frequency-domain OFDM symbol $\tilde{\mathbf{y}}_i \in \mathbb{C}^N$ at a certain receive antenna can be represented as

$$\tilde{\mathbf{y}}_i = \sum_{t=1}^{N_t} \mathrm{diag}(\tilde{\mathbf{x}}_i^{(t)}) \mathbf{F}_L \mathbf{h}_i^{(t)} + \mathbf{w}_i \tag{4}$$

where $\mathrm{diag}(\tilde{\mathbf{x}}_i^{(t)})$ is the diagonal matrix with the diagonal given by the vector $\tilde{\mathbf{x}}_i^{(t)}$, and $\mathbf{F}_L$ is the $N \times L$ partial DFT matrix composed of the first L columns of the $N \times N$ DFT matrix $\mathbf{F}$. Since the pilots patterns of different transmit antennas are orthogonal to each other, the received pilots located at $D^{(t)}$ from the t-th transmit antenna can be extracted in the frequency domain, and represented as

$$\mathbf{u}_i^{(t)} = \mathbf{F}_\mathrm{p} \mathbf{h}_i^{(t)} + \mathbf{w}_i^{(t)}, \quad 1 \le t \le N_t \tag{5}$$

where $\mathbf{u}_i^{(t)} = [\tilde{y}_{i,d_1}/\tilde{x}_{i,d_1}^{(t)}, \tilde{y}_{i,d_2}/\tilde{x}_{i,d_2}^{(t)}, \cdots, \tilde{y}_{i,d_{N_\mathrm{p}}}/\tilde{x}_{i,d_{N_\mathrm{p}}}^{(t)}]^T \in \mathbb{C}^{N_\mathrm{p}}$ denotes the pilots normalized by the transmitted original pilot power to represent channel measurements at the receiver, and $\mathbf{F}_\mathrm{p}$ is the $N_\mathrm{p} \times L$ partial DFT matrix with its entry in row-n and

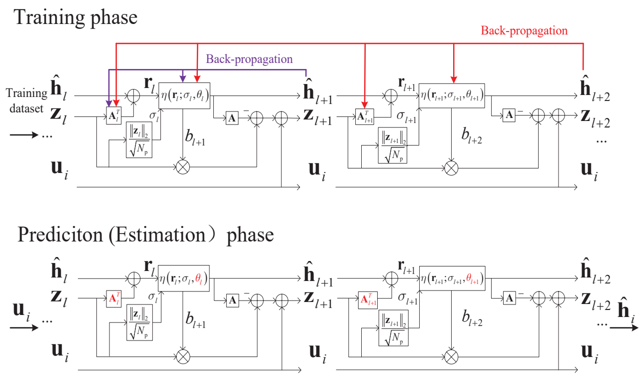

Fig. 2. The training phase and prediction (estimation) phase for massive MIMO channel estimation exploiting the LAMP networks (two layers within the LAMP networks depicted).

column-k being $\exp\left(-j2\pi d_n^{(t)}(k-1)/N\right)/\sqrt{N}$. Stacking all the channel CIRs of all the transmit antennas $\{\mathbf{h}_i^{(t)}\}_{t=1}^{N_t}$ yields the MIMO channel matrix given by $\mathbf{H}_i = [\mathbf{h}_i^{(1)}, \mathbf{h}_i^{(2)}, \cdots, \mathbf{h}_i^{(N_t)}]$.

The wireless channel is concentrated on only a few dominant taps in the delay domain, which makes the channel CIR as a sparse vector in essence [19]. Usually, the antennas of massive MIMO systems are much closer to each other compared with the propagation distance between the transmitter and the receiver, especially in the mmWave bands, so the CIRs of all transmit-receive antenna pairs share similar multipath propagation paths and characteristics, and thus share identical sparse common support in the delay domain [20]. This is called the spatial correlation of the MIMO channel, and it will facilitate the proposed algorithm as will be presented in the next section.

III. Proposed Deep Learning Based Massive MIMO Channel Estimation Scheme

In this section, two effective deep learning based MIMO channel estimation schemes are proposed for vehicular communication, utilizing the trained deep neural networks to estimate the support of the MIMO channel.

A. Deep Learning Based Channel Estimation Scheme

Considering equation (5), a sparse inverse problem is formulated, where the channel CIR $\hat{\mathbf{h}}_i$ should be recovered from the received noisy measurements $\mathbf{u}_i$ at the corresponding pilots. Different from the state-of-the-art CS-based and iterative methods for sparse recovery, a novel deep learning based channel estimation scheme of DLCE is proposed in this work to estimate the MIMO channel more accurately with much shorter delay. In the proposed DLCE scheme, the recently emerging LAMP networks [16] are well incorporated to find the support of the MIMO channel.

As illustrated in Fig. 2, the LAMP neural networks consist of N_{L} neural layers, which is used to mimic the iterative process of the sparse recovery algorithm AMP, where the linear transforms and the shrinkage functions are jointly learnt through training. The LAMP networks unfold the multiple iterations of the AMP algorithm into multiple layers of the neural networks, and decouple the linear transform denoted by the observation matrix $\mathbf{A}^T$ (let $\mathbf{A} \triangleq \mathbf{F}_{\mathrm{p}}$) to the dependent learnable parameters $\mathbf{A}_l^T$ at the l-th iteration, $l = 1, 2, \cdots N_{\mathrm{L}}$ in Fig. 2. Moreover, different layers of the networks adopt the same generic shrinkage function $\eta(\cdot)$, which is used to estimate the channel CIR $\hat{\mathbf{h}}_l$. The shrinkage function $\eta(\cdot)$ is fed by a variable (the intermediate quantities) given by $\mathbf{r}_l = \hat{\mathbf{h}}_l + \mathbf{A}_l^T \mathbf{z}_l$ and the learnable parameters $\Theta_l = \left\{\mathbf{A}_k^T, \theta_k\right\}_{k=0}^{l}$ to make the optimization tractable.

For the l-th layer of the LAMP networks, the channel CIR $\hat{\mathbf{h}}_l$ of a certain transmit-receive antenna pair in the massive MIMO system can be estimated by

$$\hat{\mathbf{h}}_{l+1} = \eta\left(\hat{\mathbf{h}}_l + \mathbf{A}_l^T \mathbf{z}_l; \sigma_l, \theta_l\right) \tag{6}$$

$$\mathbf{z}_{l+1} = \mathbf{u}_i - \mathbf{A}\hat{\mathbf{h}}_{l+1} + b_{l+1}\mathbf{z}_l \tag{7}$$

where $\hat{\mathbf{h}}_l$ and $\hat{\mathbf{h}}_{l+1}$ are the channel information at the input and output of the l-th layer, $\mathbf{z}_l$ and $\mathbf{z}_{l+1}$ denote the residual vector at the input and output of the l-th layer, $\sigma_l = \frac{\|\mathbf{z}_l\|_2}{\sqrt{N_{\mathrm{p}}}}$ can be regarded as an estimate of the standard deviation of $\mathbf{z}_l$, and θ_l is a tuning parameter of the shrinkage function.

Exploiting its iterative behavior and the capability of approaching sparse solutions, the LAMP networks are utilized to estimate the support, i.e. the locations of nonzero entries, of the MIMO channel CIRs. The pseudo-codes of the training phase and the prediction (estimation) phase of the proposed DLCE scheme are summarized in **Algorithm 1** and **Algorithm 2**, respectively. During the training phase as shown in Fig. 2, the linear transform matrix $\mathbf{A}^T$ used in the networks is decoupled into matrices $\mathbf{A}_l^T$ in multiple layers that are implicitly learnt, rather than learning some network weights directly as is done in the conventional deep learning framework. Note that the learnable parameters $\Theta_l = \left\{\mathbf{A}_k^T, \theta_k\right\}_{k=0}^{l}$ of the LAMP networks contain all layers up to and including l-layer, which are updated through back-propagation.

The training data of the LAMP networks are the noisy measurements $\mathbf{u}_i^{(t)}$ of each antenna ($t = 1, 2, \cdots N_t$) and the corresponding ground-truth channel information $\mathbf{h}_{\mathrm{true}}^{(t)}$. For each transmit antenna t, we have a training data set $\{\mathbf{u}_i^{(t),d} \in \mathbb{C}^{N_{\mathrm{P}}}\}_{d=1}^{D}$ and $\{\mathbf{h}_{\mathrm{true}}^{(t),d} \in \mathbb{C}^{L}\}_{d=1}^{D}$ to train the neural networks for the channel estimation of the corresponding MIMO sub-channel. The loss function is actually the normalized mean square error (NMSE) of the estimation, which is given by

$$\mathscr{L}_l = \frac{1}{D}\sum_{d=1}^{D} \frac{\left\|\mathbf{h}_{\mathrm{true}}^{(t),d} - f_l(\mathbf{u}_i^{(t),d}, \Theta_l)\right\|_2^2}{\left\|\mathbf{h}_{\mathrm{true}}^{(t),d}\right\|_2^2} \tag{8}$$

where $f_l(\mathbf{u}_i^{(t),d}, \Theta_l)$ denotes the channel CIR $\hat{\mathbf{h}}_l$ estimated and output by the LAMP networks composed of l layers with parameters Θ_l and input $\mathbf{u}_i^{(t),d}$. The parameters Θ_l are learnt by minimizing the loss function over the training data set $\{\mathbf{u}_i^{(t),d}\}_{d=1}^{D}$ in the training phase. The training phase is continued when the loss function $\mathscr{L}_l$ decreases with the

Algorithm 1 Deep Learning Based Channel Estimation for MIMO Systems (DLCE-Training Phase)

Input:

1) Mini-batch of size D noisy measurements $\{\mathbf{u}_i^{(t),d}\}_{d=1}^{D}$ for training of all antennas ($t = 1, 2, \cdots N_t$), the ground-truth channel information $\{\mathbf{h}_{\text{true}}^{(t),d}\}_{d=1}^{D}$

2) Observation matrix $\mathbf{A} \triangleq \mathbf{F}_{\text{p}}$

Initialization:

$\hat{\mathbf{h}}_0 \leftarrow \mathbf{0}, \mathbf{z}_{-1} \leftarrow \mathbf{0}, \mathbf{A}_0^T \leftarrow \mathbf{A}^T, b_0 \leftarrow 0$

$l \leftarrow 0$

Iterations:

repeat

  (Training for each neural network layer)

  Compute the input to shrinkage function $\mathbf{r}_l = \hat{\mathbf{h}}_l + \mathbf{A}_l^T \mathbf{z}_l$

  Generate the coarse channel estimated value $\hat{\mathbf{h}}_{l+1}$ and $\mathbf{z}_{l+1}$ by (6) and (7) with $b_{l+1} = \frac{1}{N_{\text{p}}} \sum_{j=1}^{N} \frac{\partial[\eta(\mathbf{r}_l;\sigma_l,\theta_l)]_j}{\partial \mathbf{r}_{lj}} \Big|_{\mathbf{r}_l = \hat{\mathbf{h}}_l + \mathbf{A}_l^T \mathbf{z}_l}$

  Calculate loss function $\mathscr{L}_l$ given by (8) and update $\Theta_l = \left\{\mathbf{A}_k^T, \theta_k\right\}_{k=0}^{l}$ through back-propagation using mini-batch training data

  if $\mathscr{L}_l < \mathscr{L}_{l-1}$, $l \leftarrow l+1$

until loss function does NOT decrease, i.e. $\mathscr{L}_l \geq \mathscr{L}_{l-1}$

Set final number of trained network layers as $N_{\text{L}} \leftarrow l-1$

Output:

Learned parameters $\Theta_{N_{\text{L}}} = \left\{\mathbf{A}_k^T, \theta_k\right\}_{k=0}^{N_{\text{L}}}$

Algorithm 2 Deep Learning Based Channel Estimation for MIMO Systems (DLCE-Prediction/Estimation Phase)

Input:

1) The noisy measurements $\mathbf{u}_i^{(t)}$ in (5)

2) Learned parameters $\Theta_{N_{\text{L}}} = \left\{\mathbf{A}_k^T, \theta_k\right\}_{k=0}^{N_{\text{L}}}$

Initialization:

$\hat{\mathbf{H}}_i \leftarrow \mathbf{0}_{L \times N_t}$

for $t = 1 : N_t$ **do** (prediction for each transmit antenna)

  Use trained networks with learned parameters $\Theta_{N_{\text{L}}}$ to generate the estimated channel CIR $\hat{\mathbf{h}}_i^{(t)}$ in (6)

  Select the S largest entries of $\hat{\mathbf{h}}_i^{(t)}$ to formulate dominant support $\Pi_S^{(t)} \leftarrow \max\{\hat{\mathbf{h}}_i^{(t)}, S\}$

  Estimated support $\Pi^{(t)} \leftarrow \Pi_S^{(t)}$

  Solve least squares problem:

$$\hat{\mathbf{h}}_i^{(t)}\big|_{\Pi^{(t)}} \leftarrow \mathbf{A}_{\Pi^{(t)}}^{\dagger} \mathbf{u}_i^{(t)} = (\mathbf{A}_{\Pi^{(t)}}^H \mathbf{A}_{\Pi^{(t)}})^{-1} \mathbf{A}_{\Pi^{(t)}}^H \mathbf{u}_i^{(t)}$$

  $\hat{\mathbf{h}}_i^{(t)}\big|_{\Pi^{(t)c}} \leftarrow \mathbf{0}_{(L-K)\times 1}$

end for

Output:

Estimated MIMO channel matrix

$$\hat{\mathbf{H}}_i \leftarrow \left[\hat{\mathbf{h}}_i^{(1)}, \hat{\mathbf{h}}_i^{(2)}, \cdots \hat{\mathbf{h}}_i^{(N_t)}\right]$$

increase of the number of layers l, which means that the more network capacity will better approach the ground-truth channel and the generalization capability is improved. The training phase terminates when the loss function does NOT decrease anymore with the number of layers, i.e. $\mathscr{L}_l \geq \mathscr{L}_{l-1}$, since at this moment overfitting might have occurred and we have successfully found the best network structure (number of layers) with the optimal capacity, i.e. $N_{\text{L}} \leftarrow l-1$. This criterion therein is utilized to determine the hyperparameter l and the network depth, which might have played a similar role as the validation set, which is also utilized for preventing overfitting.

With the trained LAMP network, the MIMO channel can be estimated accurately in the subsequent prediction phase. First, the channel CIRs for each antenna are estimated respectively using the trained LAMP networks. Then, the S largest entries in the estimated CIR formulate the dominant support $\Pi_S^{(t)}$, where S can be chosen and adjusted properly according to the empirically set threshold [18]. The desired estimated support is then obtained, i.e. $\Pi^{(t)} \leftarrow \Pi_S^{(t)}$. Then the originally intractable under-determined problem given by (5) can be turned into an least squares (LS) problem to obtain the amplitude of the nonzero entries at the support, and thus the CIR $\mathbf{h}_i^{(t)}$ for the t-th transmit antenna is achieved. Finally, the MIMO channel matrix containing N_t CIRs can be represented as

$$\hat{\mathbf{H}}_i = \left[\hat{\mathbf{h}}_i^{(1)}, \hat{\mathbf{h}}_i^{(2)}, \cdots, \hat{\mathbf{h}}_i^{(N_t)}\right] \tag{9}$$

Due to the utilization of the LAMP networks, the proposed DLCE scheme is able to predict the massive MIMO channels more stably and more accurately than the conventional CS-based methods. Moreover, since the prediction phase only requires an end-to-end feed-forward calculation in the neural networks rather than a large number of iterations, the proposed DLCE scheme costs much shorter delay than the CS-based and iterative schemes.

B. Spatially Correlated Deep Learning Based Massive MIMO Channel Estimation Scheme

The DLCE scheme estimates the CIR for each antenna separately and does not consider the inter-antenna correlation, so the performance is limited for MIMO systems with spatial correlation. To further improve the estimation accuracy of massive MIMO channels, the SC-DLCE scheme is devised, which jointly estimates the CIRs of different antennas by utilizing the spatial correlation of the MIMO channel.

Stacking by column all the channel measurements $\mathbf{u}_i^{(t)}$, $t = 1, 2, \cdots N_t$, the received MIMO channel measurements matrix can be represented as

$$\mathbf{U}_i = \left[\mathbf{u}_i^{(1)}, \mathbf{u}_i^{(2)}, \cdots, \mathbf{u}_i^{(N_t)}\right] \tag{10}$$

Specifically, the CIRs for each antenna is predicted first by the LAMP networks in the SC-DLCE scheme, which is similar to the training procedure of DLCE. Since the channels of different antennas share the same support due to the spatial correlation as described in Section II, the SC-DLCE algorithm will be approaching the ground-truth channel information in the training phase more rapidly. In the prediction phase, by obtaining the intersection of the CIRs predicted for all the N_t antennas, the spatially correlated common support for the SC-DLCE scheme can be generated as

$$\bar{\Pi}_S = \bigcap_{t=1}^{N_t} \Pi^{(t)} \tag{11}$$

Then, by obtaining the MIMO channel desired support $\bar{\Pi} \leftarrow \bar{\Pi}_S$, the corresponding channel amplitude can be directly estimated by solving the formulated multiple measurement LS problem as

$$(\hat{\mathbf{H}}_i)^T|_{\bar{\Pi}} \leftarrow \left(\mathbf{A}_{\bar{\Pi}}^{\dagger}\mathbf{U}_i\right)^T = \left(\left(\mathbf{A}_{\bar{\Pi}}^H\mathbf{A}_{\bar{\Pi}}\right)^{-1}\mathbf{A}_{\bar{\Pi}}^H\mathbf{U}_i\right)^T \tag{12}$$

Compared with the DLCE scheme, the desired support of the MIMO channel in the SC-DLCE scheme is more accurately obtained by jointly considering the contributions of all the MIMO channels at different spatially located antennas. Hence, the enhanced SC-DLCE scheme has an advantage in the accuracy of MIMO channel estimation over the DLCE scheme, especially in the low SNR region. Moreover, the required additional operation given by (11) only involves a low complexity calculation, which shows the efficiency of the proposed enhanced scheme.

IV. Simulation Results

In this section, the performance of the proposed DL-based MIMO channel estimation schemes is evaluated through simulations, and also compared with the state-of-the-art schemes for the massive MIMO enabled vehicular communication scenarios. The simulation parameters are summarized as follows. The system bandwidth is $B = 8$ MHz, located at the central frequency of $f_c = 780$ MHz. The number of OFDM sub-carriers and the preamble length are $N = 4096$ and $M = 256$, respectively. The maximum delay spread length of the vehicular communications multipath channel, which is to be estimated, is $L = 256$ [21]. The number of pilots for channel measurements in the frequency domain is set as $N_p = 25$. The antenna scale of the MIMO system is $N_t = N_r = 32$.

The training data sets $\{\mathbf{u}_i^{(t),d} \in \mathbb{C}^{N_p}\}_{d=1}^D$ and $\{\mathbf{h}_{\text{true}}^{(t),d} \in \mathbb{C}^L\}_{d=1}^D$, with $D = 2000$, are randomly generated, where each training sample d in the training data set includes a ground-truth CIR vector $\mathbf{h}_{\text{true}}^{(t)}$ and the corresponding pilot measurement vector $\mathbf{u}_{\text{true}}^{(t)}$ obtained based on (5). The channel support of the CIR vector $\mathbf{h}_i^{(t)}$ of each training sample can be uniformly distributed in the L delay taps and the amplitude follows a Rayleigh fading distribution [19]. The testing data sets for evaluation are generated in a similar way, i.e. the CIR vectors and the pilot measurement vectors are randomly generated. The observation matrix is a partial DFT matrix $\mathbf{A} \triangleq \mathbf{F}_p \in {}^{N_p \times L}$. The learning rate of the training phase is set to $\alpha = 10^{-3}$. The parameters are learnt by minimizing the loss function given by (8) over the training data sets, and the gradient descent method and the Adam optimizer are utilized

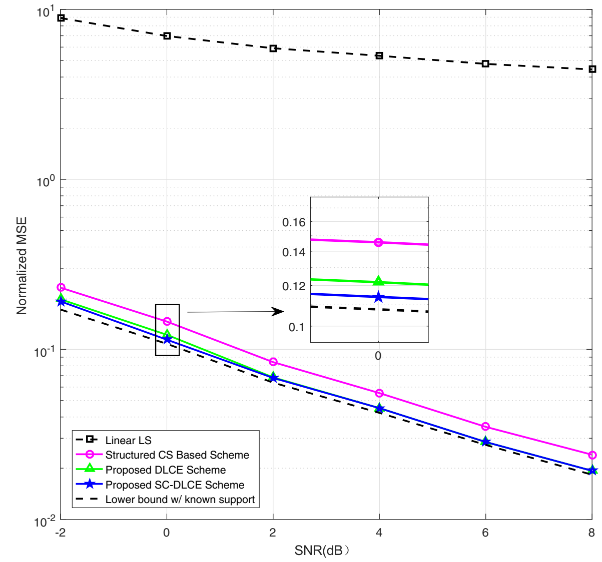

Fig. 3. NMSE performance comparison of the proposed deep learning based schemes and the state-of-the-art benchmark schemes for 32×32 MIMO channel estimation.

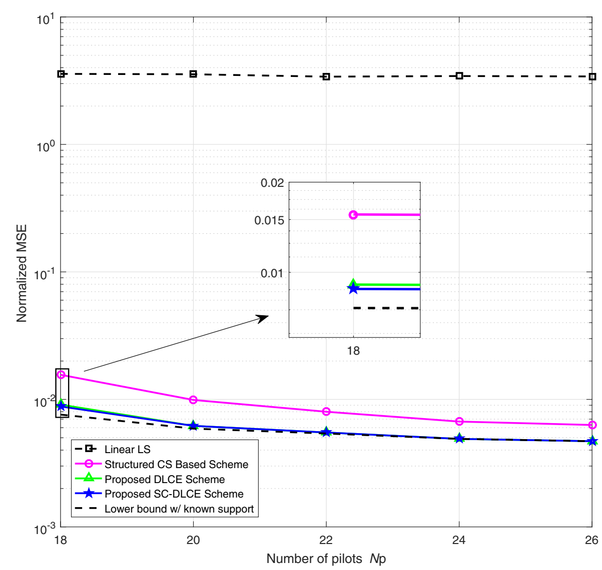

Fig. 4. Comparison of the NMSE performance with different number of pilots as channel measurement data at SNR = 15 dB.

to train the LAMP networks. Note that the number of layers of the LAMP networks should be decided properly based on the validation set performance in order to avoid overfitting in the phase of training.

The NMSE performance comparison of different schemes under the vehicular multipath fading channel in 32×32 MIMO systems, is reported in Fig. 3 to show the accuracy of different channel estimation schemes. The state-of-the-art structured CS-based MIMO channel estimation method [10] utilizing the structured CS algorithm of SOMP [22], where the same number of pilots is adopted, is evaluated for comparison, which is a representative benchmark scheme for CS-based methods since structured CS is an enhanced CS framework.

It can be noted from Fig. 3 that, the proposed DLCE and SC-DLCE schemes outperform the state-of-the-art CS-based method by approximately 0.6 dB and 0.8 dB, respectively, in the 32×32 MIMO system. With the increase of SNR, the estimated channel obtained through the LAMP networks in the two schemes become more and more accurate, and finally approaches a lower bound (as indicated by a black dotted line) obtained by assuming perfect support available at the receiver, i.e. the NMSE is caused by only background noise in the pilots. It is also demonstrated that the SC-DLCE scheme has better performance of MIMO channel estimation compared with the DLCE scheme, especially in the low SNR region, since the spatial correlation is fully exploited to estimate the MIMO channel more stably and more accurately.

In addition, the NMSE performance comparison for the channel estimation schemes with respect to different number of pilots, i.e. size of channel measurement data, at the SNR of 15 dB in a wireless vehicular 16×16 MIMO communication system is depicted in Fig. 4. Compared with the state-of-the-art structured CS-based method, the proposed DL-based schemes are able to achieve a much higher channel estimation accuracy with only a small number of available pilots, which greatly improves the spectrum efficiency of the massive MIMO system, especially reducing the requirement of orthogonally patterned pilots greatly for large antenna arrays. Moreover, since the implementation of the proposed schemes only needs to conduct a single-trip forward propagation in the trained neural networks in realistic channel estimation scenarios rather than a time-consuming iterative process of CS-based methods, the two proposed schemes have much shorter delay than the CS-based and iterative schemes.

V. Conclusion

In this paper, a novel DL-based massive MIMO channel estimation scheme has been proposed by exploiting the neural networks to estimate the sophisticated multipath fading MIMO channels with much higher accuracy and much smaller delay than state-of-the-art conventional, iterative and CS-based methods. To further improve the estimation accuracy for massive antenna arrays, especially in the low SNR environment, an enhanced scheme of SC-DLCE has been proposed to make full use of the spatial correlation between the massive antennas for a more robust recovery of the channel support. Simulation results have verified that, the two proposed DL-based schemes can significantly improve the accuracy of MIMO channel estimation compared with the state-of-the-art benchmark schemes in realistic vehicular communications scenarios. Furthermore, the proposed DL-based sparse recovery framework is promising in other communication systems with high accuracy and stringent low-latency requirements.

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