Deep Learning Based Underwater Acoustic Channel Estimation Exploiting Physical Knowledge on Channel Sparsity

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ABSTRACT

It is well known that the underwater acoustic channel (UAC) has the physical characteristic of sparse structure due to the significant multipath effect. To improve the performance of UAC estimation, with the physical knowledge on channel sparsity in mind we propose a novel method called Deep Learning based UAC Estimation (DL-UACE) in this paper. The DL-UACE method combines the conventional iterative sparse recovery algorithm of approximate message passing (AMP) with deep neural network (DNN) to construct a sparsity-aware DNN for the deep learning of the inherent sparse structure of the UAC. Furthermore, the denoising convolutional neural network (DnCNN) is integrated into the sparsity-aware DNN as a denoiser to mitigate the impact of ubiquitous ambient noise that obeys Gaussian distribution on UAC estimation. Simulation results show that the proposed DL-UACE method is superior to the state-of-the-art methods in terms of estimation accuracy and spectrum efficiency, especially in severe conditions of low signal-to-noise ratio (SNR) or insufficient pilots.

KEYWORDS

Underwater acoustic channel, Sparse recovery, Deep learning, Deep neural network, Denoising

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1 INTRODUCTION

Underwater acoustic channel (UAC) estimation, whose goal is to obtain accurate channel state information (CSI), is still a challenging problem for underwater acoustic orthogonal frequency division multiplexing (UA-OFDM) communication systems [18]. Most difficulties arise from the complicated characteristics of the UAC, such as time varying, multipath fading, delay spread, and Doppler spread, etc [20]. Fortunately, in addition to the above characteristics, the UAC is well known to usually have a sparse structure in the sense that the channel energy is principally concentrated in only a few dominant paths, which greatly reduces the number of channel coefficients that need to be estimated [2, 20]. Thus, exploiting the physical knowledge on channel sparsity is the key to improving the performance of channel estimation [2, 15, 18].

In recent decades, vast UAC estimation methods have been extensively studied based on various adaptive algorithms, which can be classified into two categories: the traditional methods and the compressed sensing (CS) based methods. The traditional methods, mainly including least square (LS) [19] and minimum mean square error (MMSE) [26] methods, are generally easy to implement but cannot effectively exploit the channel sparsity, which results in high overhead of spectrum resources and limited estimation accuracy [19, 26]. The CS-based methods mainly include convex optimization algorithms (e.g., basis pursuit [10] and approximate message passing (AMP) [8]) and greedy algorithms, the latter of which has been well investigated in the area of sparse UAC estimation, including orthogonal matching pursuit (OMP) and many related improved greedy algorithms [6, 7, 13, 14, 22, 23].

Wan *et al*. [22] proposed an OMP-based UAC estimation scheme using equispaced pilots, which achieves a considerable improvement in estimation accuracy compared with the traditional methods. Chen *et al*. [6] applied compressive sampling matching pursuit (CoSaMP) to estimate the coefficients of the UAC with the sparsity level as a priori knowledge. Different from CoSaMP, the sparse adaptive matching pursuit (SAMP) algorithm proposed in [7], which has a step size to adjust the sparsity level, can estimate the sparse UAC coefficients without requiring the sparsity level. Although the CS-based methods can effectively make up for the deficiencies of the traditional methods by exploiting the channel sparsity, the performance may degrade in the case of intensive ambient noise or insufficient pilots [1, 5].

Recently, advances in deep learning (DL) techniques have facilitated the rapid development of many fields, such as sparse recovery [4, 11, 12, 17] and massive MIMO communications [9, 24], which also provide a new solution for UAC estimation. Consequently, utilizing the theory of CS and DL, with the physical knowledge on channel sparsity in mind we combine AMP with deep neural network (DNN) to propose a Deep Learning based UAC Estimation (DL-UACE) method to improve the performance of UAC estimation in this paper. Specifically, we decompose the conventional iterative sparse recovery algorithm of AMP into several differently parameterized layers of a sparsity-aware DNN to learn the inherent sparse structure of the UAC and facilitate the UAC estimation.

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Furthermore, considering the ubiquitous ambient noise that obeys Gaussian distribution during the channel measurements, we integrate the denoising convolutional neural network (DnCNN) [25] into the sparsity-aware DNN as a denoiser to reduce the estimation error caused by Gaussian noise and further improve the estimation accuracy.

The rest of this paper is organized as follows: Section 2 presents the system model. Section 3 proposes the DL-UACE method for UAC estimation exploiting the channel sparsity as a physical prior knowledge. Section 4 reports the simulation results. Finally, Section 5 concludes this paper.

2 SYSTEM MODEL

In typical UA-OFDM communication systems, the channel impulse response (CIR) of the time-varying UAC with P paths based on the ray theory can be expressed as [2, 20, 27]

$$h(t;\tau) = \sum_{i=1}^{P} A_i(t)\delta\left(\tau - \tau_i(t)\right), \tag{1}$$

where $A_i(t)$ and $\tau_i(t)$ denote the time varying amplitude and delay of the i-th path, respectively. Within the duration of each OFDM block, the following commonly recognized assumption on the UAC is adopted [2, 5, 18]: the channel coefficients are treated as approximately constant and the channel is approximately considered as time-invariant, since the coherence time of the channel is usually much longer than the symbol period of the system. Therefore, the CIR of the UAC with L taps in the discrete time domain can be represented as [2, 23]

$$\mathbf{h} = [h_1, h_2, \ldots, h_L]^{\mathrm{T}}. \tag{2}$$

It is notable that due to the inherent sparse structure of the UAC, the amplitude of the dominant K paths is non-zero, and the amplitude of other paths is either zero or relatively quite small [2, 18, 20]. Thus, the CIR of the UAC is assumed to be K-sparse ($K \ll L$).

The block transmission scheme of cyclic prefix OFDM (CP-OFDM) is considered in this paper to relieve multipath fading and intersymbol interference (ISI) [1, 5]. Assume that there are N_c subcarriers in an OFDM block, among which N_p ($N_\mathrm{p} < N_\mathrm{c}$) subcarriers are employed to carry pilot symbols for channel estimation. Then according to the pilot assisted channel estimation method, the UAC estimation problem can be formulated in the frequency domain as [2, 23]

$$\begin{aligned} \mathbf{y} &= \mathbf{X}\,\tilde{\mathbf{h}} + \mathbf{n} \\ &= \mathbf{X}\,\mathbf{F}_\mathrm{p}\,\mathbf{h} + \mathbf{n} \\ &= \mathbf{A}\,\mathbf{h} + \mathbf{n}, \end{aligned} \tag{3}$$

where $\mathbf{y} = \left[y_1, y_2, \ldots, y_{N_\mathrm{p}}\right]^{\mathrm{T}}$ is the received pilots regarded as the measurement vector in the CS framework. $\mathbf{X} = \mathrm{diag}\left(x_1, x_2, \ldots, x_{N_\mathrm{p}}\right)$ is a diagonal matrix that takes the transmitted pilots as diagonal elements. $\tilde{\mathbf{h}} = \mathbf{F}_\mathrm{p}\,\mathbf{h}$ is the channel frequency response. $\mathbf{F}_\mathrm{p}$ denotes the normalized partial discrete Fourier transform (DFT) matrix with size $N_\mathrm{p} \times L$, which is composed of the N_p rows corresponding to the pilot position and the first L columns of the original $N_\mathrm{c} \times N_\mathrm{c}$ DFT matrix. The matrix $\mathbf{A} = \mathbf{X}\,\mathbf{F}_\mathrm{p}$ with size $N_\mathrm{p} \times L$ is referred to as the measurement matrix in the CS framework. $\mathbf{n} = \left[n_1, n_2, \ldots, n_{N_\mathrm{p}}\right]^{\mathrm{T}}$ is the additive white Gaussian noise (AWGN) [1].

In the CS framework, utilizing the measurement matrix $\mathbf{A}$ and the measurement vector $\mathbf{y}$, the UAC estimation problem can be formulated as a sparse recovery problem given by (3) and the unknown CIR $\mathbf{h}$ of the UAC can be reconstructed using classical sparse recovery methods, including iterative sparse recovery algorithms and CS-based greedy algorithms, etc. In order to further improve the performance of UAC estimation against severe underwater channel environments, a sparsity-aware DNN based method of UAC estimation is proposed with a denoising CNN to mitigate the impact of the intensive ambient noise, which is described in detail in the next section.

3 SPARSITY-AWARE DEEP LEARNING WITH DENOISING FOR UAC ESTIMATION

In the proposed Deep Learning based UAC Estimation (DL-UACE) method, first we decompose the conventional iterative sparse recovery algorithm of AMP into several differently parameterized layers of a sparsity-aware DNN to learn the inherent sparse structure of the UAC and facilitate the UAC estimation [4]. Furthermore, considering the ubiquitous ambient noise that follows a Gaussian distribution additive on the channel measurements, we integrate a denoising CNN (DnCNN) [25] into the devised sparsity-aware DNN as a denoiser to mitigate the impact of Gaussian noise on UAC estimation [16, 17]. The architecture of the devised sparsity-aware DNN with DnCNN is shown in Figure 1.

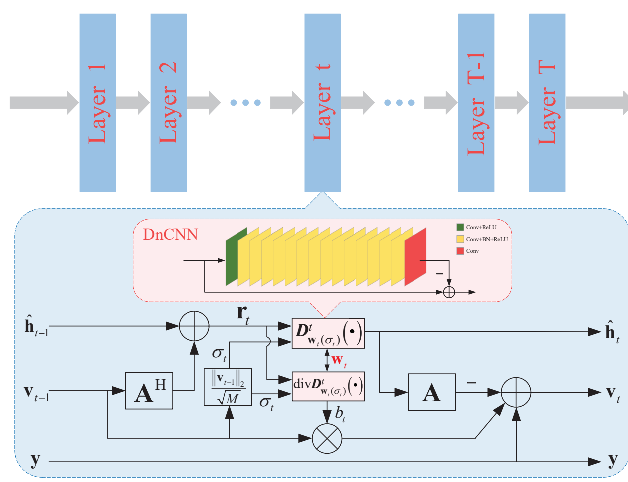

Figure 1: The sparsity-aware DNN consists of T cascaded layers with identical structure, in which each layer contains two identical denoisers, i.e. DnCNNs, with the same weights.

The implementation of the DL-UACE method in estimating the CIR of the UAC includes two stages: the training stage and the estimation stage, both of which are summarized in Algorithm 1 and Algorithm 2, respectively.

In Algorithm 1, $\mathbf{v}_t$ denotes the residual measurement error of the t-th layer. $\hat{\mathbf{h}}_t$ denotes the estimation result of the t-th layer. $\mathbf{z}_t$

Algorithm 1: DL-UACE – Training stage.

Input: training dataset $\left\{(\mathbf{y}^d, \mathbf{h}^d)\right\}_{d=1}^{D}$ with size D, which is composed of the measurement vector $\mathbf{y}$ and the corresponding ground-truth CIR $\mathbf{h}$; measurement matrix $\mathbf{A}$.
Initialization: $M = N_\text{p}$, $N = L$, $\mathbf{v}_0 = \mathbf{0}$, $\hat{\mathbf{h}}_0 = \mathbf{0}$.
/* Training the DNN layer-wise. */
for $t = 1, 2, 3, \ldots$ **do**
1: Initialize the learnable parameter $\mathbf{w}_t$ of the denoiser with a standard normal random vector, $\mathbf{w}_t \sim \mathcal{N}\left(\mathbf{0}, \mathbf{I}_{N_\text{D}}\right)$.
2: Compute the estimated standard deviation of the effective noise via $\sigma_t \leftarrow \frac{1}{\sqrt{M}} \|\mathbf{v}_{t-1}\|_2$.
3: Compute the input of the denoiser via $\mathbf{r}_t \leftarrow \hat{\mathbf{h}}_{t-1} + \mathbf{A}^\text{H}\mathbf{v}_{t-1}$.
4: Update the estimation result of the UAC via $\hat{\mathbf{h}}_t \leftarrow \boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}\left(\hat{\mathbf{h}}_{t-1} + \mathbf{A}^\text{H}\mathbf{v}_{t-1}\right)$.
5: Compute the scalar b_t via Monte-Carlo approximation, $b_t \leftarrow \frac{1}{M}\text{div}\boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}\left(\hat{\mathbf{h}}_{t-1} + \mathbf{A}^\text{H}\mathbf{v}_{t-1}\right)$.
6: Update the residual measurement error via $\mathbf{v}_t \leftarrow \mathbf{y} - \mathbf{A}\hat{\mathbf{h}}_t + b_t\mathbf{v}_{t-1}$.
7: Use back propagation and stochastic gradient descent to update and optimize the learnable parameter $\mathbf{w}_t$ to minimize the loss $L_t(\Theta)$ in (5).
8: **If** $L_t(\Theta) \geqslant L_{t-1}(\Theta)$, **then** the number of layers is finalized as $T \leftarrow t - 1$ and **break**.
end
Output: learned parameters $\Theta = \left\{\{\mathbf{w}_t\}_{t=1}^T\right\}$.

denotes the effective noise of the t-th layer, which is the difference between the input $\hat{\mathbf{h}}_{t-1} + \mathbf{A}^\text{H}\mathbf{v}_{t-1}$ of the denoiser and the ground-truth CIR $\mathbf{h}$ provided by the training data sample, i.e., $\mathbf{z}_t = \hat{\mathbf{h}}_{t-1} + \mathbf{A}^\text{H}\mathbf{v}_{t-1} - \mathbf{h}$, where $\mathbf{A}^\text{H}$ denotes the conjugate transpose of the measurement matrix $\mathbf{A}$. σ_t denotes the estimated standard deviation of the effective noise $\mathbf{z}_t$, which depends on $\mathbf{v}_{t-1}$. $b_t\mathbf{v}_{t-1}$ is the Onsager correction term [3], which forces the effective noise in each layer to be distributed very close to Gaussian noise and accelerates the convergence of the estimation result [4, 16, 17]. Hence, the effective noise $\mathbf{z}_t = \sigma_t\boldsymbol{\epsilon} \sim \mathcal{N}\left(\mathbf{0}, \sigma_t^2\mathbf{I}_N\right)$, where $\boldsymbol{\epsilon} \sim \mathcal{N}\left(\mathbf{0}, \mathbf{I}_N\right)$ [16].

As far as the DnCNN is concerned, $\boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}$ denotes the denoiser incorporated in the t-th layer, whose learnable weight $\mathbf{w}_t$ is related to σ_t. Note that in each layer of the DNN, the input of the denoiser can be regarded as the ground-truth CIR plus the effective noise, i.e., $\hat{\mathbf{h}}_{t-1} + \mathbf{A}^\text{H}\mathbf{v}_{t-1} = \mathbf{h} + \mathbf{z}_t = \mathbf{h} + \sigma_t\boldsymbol{\epsilon}$. Thus, the denoiser $\boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}$ is fed by $\hat{\mathbf{h}}_{t-1} + \mathbf{A}^\text{H}\mathbf{v}_{t-1}$ as the input, and yields the estimation result $\hat{\mathbf{h}}_t$ as the output to implement the denoising of the effective noise $\mathbf{z}_t$ [16], as depicted in step 4 of Algorithm 1. $\text{div}\boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}$ is the divergence of the denoiser $\boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}$, which is estimated by the following Monte-Carlo approximation [21],

$$\text{div}\boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}(\cdot) \approx \frac{\mathbf{u}^\text{T}}{c}\left(\boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}(\cdot + c\mathbf{u}) - \boldsymbol{D}^t_{\mathbf{w}_t(\sigma_t)}(\cdot)\right), \tag{4}$$

where $\mathbf{u} \sim \mathcal{N}(0, \mathbf{I}_N)$ is a standard normal random vector and $c > 0$ is a small positive number.

As for the training process and dataset, $\left\{(\mathbf{y}^d, \mathbf{h}^d)\right\}_{d=1}^{D}$ denotes the training dataset with size D, where $\mathbf{y}^d$ and $\mathbf{h}^d$ are the measurement vector and the corresponding ground-truth CIR of the d-th training data sample, respectively. The training dataset is composed of $(feature, label)$ pairs, using which the learnable parameters Θ of the DNN is trained via minimizing the mean square error (MSE) loss function as

$$L_t(\Theta) = \frac{1}{D}\sum_{d=1}^{D}\left\|\mathbf{h}^d - \hat{\mathbf{h}}_t\left(\mathbf{y}^d, \Theta\right)\right\|_2^2. \tag{5}$$

The main setps of the training stage of the DL-UACE method are summarized in Algorithm 1. In the training stage, the learnable parameters Θ of the DNN are the weights $\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_T$ of the denoisers, i.e., $\Theta = \left\{\{\mathbf{w}_t\}_{t=1}^T\right\}$. We train the DNN layer-wise to obtain the optimal learnable parameters: first we train a DNN with only one layer to minimize $L_1(\Theta)$, and then the second layer is added and the resulting two-layer DNN is trained to minimize $L_2(\Theta)$. Repeat the similar process until the T-layer DNN has been trained to minimize $L_t(\Theta)$. Note that when we train a certain t-th layer, $t = 1, 2, \ldots, T$, all the parameters of the previous $t - 1$ layers are kept fixed. During this process, the learnable parameters Θ can be updated and optimized by using back propagation and stochastic gradient descent to minimize the loss of (5). When the loss stops decreasing with the number of layers, i.e., $L_t(\Theta) \geqslant L_{t-1}(\Theta)$, overfitting may have occurred at this moment, and thus the optimal number of layers can be finalized to $T \leftarrow t - 1$ and the learned parameters Θ have been obtained, which ends the training stage.

Algorithm 2: DL-UACE – Estimation stage.

Input: measurement vector $\mathbf{y}$; measurement matrix $\mathbf{A}$; number of layers T; network parameters Θ learned in the training stage.
Initialization: $M = N_\text{p}$, $N = L$, $\mathbf{v}_0 = \mathbf{0}$, $\hat{\mathbf{h}}_0 = \mathbf{0}$, $\hat{\mathbf{h}} = \mathbf{0}$.
1: Input $\mathbf{y}$ and $\mathbf{A}$ to the well-trained T-layer DNN with learned parameters Θ to estimate the coarse CIR $\hat{\mathbf{h}}_T = \boldsymbol{D}^T_{\mathbf{w}_T(\sigma_T)}\left(\hat{\mathbf{h}}_{T-1} + \mathbf{A}^\text{H}\mathbf{v}_{T-1}\right)$ through a one-way feed-forward propagation.
2: Select the indices of the K largest entries in $\hat{\mathbf{h}}_T$ to estimate the dominant sparse support $\Omega = \mathbb{S}\left(\hat{\mathbf{h}}_T, K\right)$.
3: Use the LS method to compute the amplitude of the non-zero entries corresponding to the sparse support Ω, so as to obtain the accurate CIR, i.e., $\hat{\mathbf{h}} = \mathbf{A}_\Omega^\dagger\mathbf{y} = \left(\mathbf{A}_\Omega^\text{H}\mathbf{A}_\Omega\right)^{-1}\mathbf{A}_\Omega^\text{H}\mathbf{y}$.
Output: UAC estimation result $\hat{\mathbf{h}}$.

As summarized in Algorithm 2, in the estimation stage, the well-trained DNN is employed to estimate the sparse support of the CIR through a one-way feed-forward propagation. The indices of the K largest entries in the estimated coarse CIR $\hat{\mathbf{h}}_T$, which is the output of the well-trained DNN, are selected to estimate the dominant sparse support Ω. The support Ω is a set that contains the indices of the K largest entries in $\hat{\mathbf{h}}_T$. $\mathbb{S}\left\{\hat{\mathbf{h}}_T, K\right\}$ denotes the operator that selects the indices of the K largest entries in the sparse vector of $\hat{\mathbf{h}}_T$. Finally, the accurate amplitude of the non-zero entries corresponding to the sparse support Ω is computed by using the simple LS method, so as to obtain the accurate UAC estimation result $\hat{\mathbf{h}}$. $\mathbf{A}_\Omega$ denotes a $M \times N$ matrix generated by the measurement matrix $\mathbf{A}$ with the columns indexed by the set Ω remained and other columns set to all zeros. $(\cdot)^\dagger$ and $(\cdot)^H$ denote the Moore-Penrose pseudoinverse and conjugate transpose, respectively.

Since the sparsity-aware DNN in the DL-UACE method can by best effort utilize a large amount of training data to learn the sparse structure of the UAC through deep learning, and exploit the denoiser to reduce the estimation error caused by Gaussian noise, the accuracy of UAC estimation can be significantly improved, especially in harsh conditions of low signal-to-noise ratio (SNR) or insufficient pilots. The simulation results in the next section have verified the superior performance of the proposed DL-UACE method over conventional ones.

4 SIMULATION RESULTS

In this section, we evaluate the performance of the proposed DL-UACE method through numerical simulations. The main simulation parameters of the UA-OFDM system are listed in Table 1.

Table 1: Simulation Parameters

Parameter	Value
Carrier Frequency	12kHz
Bandwidth	8kHz
Number of Subcarriers	1024
CP Length	256
Number of Pilots	64
Channel Length	256
Number of Channel Paths	8
Ambient Noise	AWGN

The training dataset $\left\{(\mathbf{y}^d, \mathbf{h}^d)\right\}_{d=1}^{D}$ with size $D = 2000$ is randomly generated according to the underwater acoustic statistical channel distribution described in [27], and the test dataset is generated in a similar way. In the training stage, we train the sparsity-aware DNN layer-wise with a learning rate $\gamma = 0.001$ and utilize the Adam optimizer to optimize the learnable parameters $\mathbf{\Theta}$. After several training epochs, the optimal number of layers is converged to T, and the learned parameters $\mathbf{\Theta} = \left\{\{\mathbf{w}_t\}_{t=1}^{T}\right\}$ are obtained.

We compare the proposed DL-UACE method with the state-of-the-art UAC estimation methods, including the classical LS [19] method, the iterative sparse recovery algorithm of AMP [8], and the CS-based greedy algorithms of OMP [22], SAMP [7], and CoSaMP [6]. For the LS, OMP and CoSaMP methods, the default parameters are configured; For the AMP method, in order to ensure the convergence of the estimation result, the maximum number of iterations is set to 30; For the SAMP method, the step size parameter is set to 1. The normalized MSE (NMSE) is used as a performance metric, which is defined as $\|\mathbf{h} - \hat{\mathbf{h}}\|_2^2 / \|\mathbf{h}\|_2^2$, where $\hat{\mathbf{h}}$ denotes the estimation result and $\|\cdot\|_2$ denotes the l_2 norm.

Figure 2 compares the NMSE performance of different UAC estimation methods versus different SNR values using 64 pilots

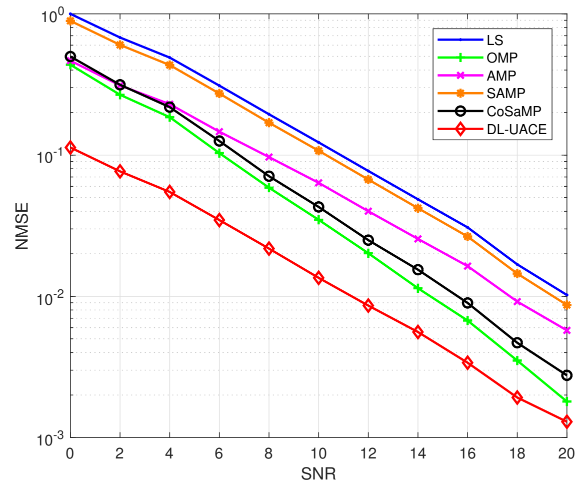

Figure 2: Comparison of NMSE performance of different UAC estimation methods with respect to different SNR values.

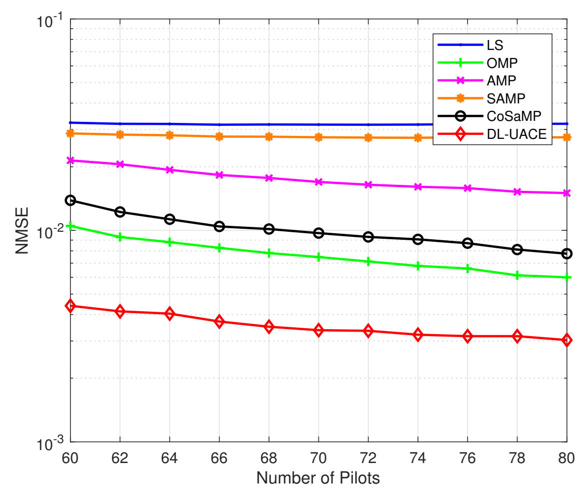

Figure 3: Comparison of NMSE performance of different UAC estimation methods with respect to the number of available pilots.

for channel estimation. It can be observed that, the proposed DL-UACE method significantly outperforms the benchmark methods in estimation accuracy, especially in the low SNR region. At the target NMSE level of 10^{-2}, the proposed DL-UACE method has a SNR gain of 3dB, 4dB and 6dB over the OMP, CoSaMP, and AMP methods, respectively, which indicates the superior performance of the sparsity-aware DNN with denoising. The simulation results have verified that the sparsity-aware DNN in the DL-UACE method can effectively exploit the physical prior knowledge on the channel sparsity, i.e., learn the sparse structure of the UAC, and utilize the denoiser to reduce the estimation error caused by Gaussian noise. Besides, the simulation results have also revealed the superiority of DL techniques and data-driven approaches over conventional ones.

The NMSE performance comparison of different UAC estimation methods with respect to the number of available pilots at the SNR of 15dB is reported in Figure 3. It can be observed from the simulation results that, compared with the existing methods of LS, OMP, AMP, SAMP and CoSaMP, the proposed DL-UACE method can achieve a higher accuracy of UAC estimation with much less overhead of pilots, thus significantly improving the spectrum efficiency.

5 CONCLUSION

In this paper, we propose a DL-UACE method that combines the physical knowledge on channel sparsity with the data-driven approach to improve the performance of UAC estimation. Particularly, we use the UAC dataset to train a sparsity-aware DNN with Gaussian denoising to learn the inherent sparse structure of the UAC, aiming to improve the estimation accuracy and spectral efficiency. Simulation results demonstrate that the proposed DL-UACE method significantly outperforms the state-of-the-art methods in terms of estimation accuracy and spectrum efficiency of UAC estimation, especially in harsh circumstances of low SNR or insufficient pilots. The proposed DL-UACE method is promising to be applied in underwater acoustic communication systems where accurate and efficient channel estimation is prioritized.

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REFERENCES

[1] S. Banerjee and M. Agrawal. 2013. Underwater acoustic noise with generalized Gaussian statistics: Effects on error performance. In *2013 MTS/IEEE OCEANS - Bergen*. 1–8.

[2] C. R. Berger, S. Zhou, J. C. Preisig, and P. Willett. 2010. Sparse channel estimation for multicarrier underwater acoustic communication: From subspace methods to compressed sensing. *IEEE Trans. Signal Process.* 58, 3 (2010), 1708–1721.

[3] M. Borgerding and P. Schniter. 2016. Onsager-corrected deep learning for sparse linear inverse problems. In *2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*. 227–231.

[4] M. Borgerding, P. Schniter, and S. Rangan. 2017. AMP-inspired deep networks for sparse linear inverse problems. *IEEE Trans. Signal Process.* 65, 16 (2017), 4293–4308.

[5] P. Chen, Y. Rong, S. Nordholm, Z. He, and A. J. Duncan. 2017. Joint channel estimation and impulsive noise mitigation in underwater acoustic OFDM communication systems. *IEEE Trans. Wireless Commun.* 16, 9 (2017), 6165–6178.

[6] Y. Chen, C. Clemente, J. Soraghan, and S. Weiss. 2016. Fractional Fourier based sparse channel estimation for multicarrier underwater acoustic communication system. In *2016 Sensor Signal Processing for Defence (SSPD)*. 1–5.

[7] T. T. Do, L. Gan, N. Nguyen, and T. D. Tran. 2008. Sparsity adaptive matching pursuit algorithm for practical compressed sensing. In *2008 42nd Asilomar Conference on Signals, Systems and Computers (ACSSC)*. 581–587.

[8] D. L. Donoho, A. Maleki, and A. Montanari. 2010. Message passing algorithms for compressed sensing: II. analysis and validation. In *2010 IEEE Information Theory Workshop on Information Theory (ITW 2010, Cairo)*. 1–5.

[9] H. He, C. Wen, S. Jin, and G. Y. Li. 2018. Deep learning-based channel estimation for beamspace mmwave massive MIMO systems. *IEEE Wireless Commun. Lett.* 7, 5 (2018), 852–855.

[10] J. Huang, C. R. Berger, S. Zhou, and J. Huang. 2010. Comparison of basis pursuit algorithms for sparse channel estimation in underwater acoustic OFDM. In *OCEANS'10 IEEE SYDNEY*. 1–6.

[11] S. Liu, L. Xiao, Z. Han, and Y. Tang. 2019. Eliminating NB-IoT interference to LTE system: A sparse machine learning-based approach. *IEEE Internet Things* 6, 4 (2019), 6919–6932.

[12] S. Liu, L. Xiao, L. Huang, and X. Wang. 2019. Impulsive noise recovery and elimination: A sparse machine learning based approach. *IEEE Trans. Veh. Technol.* 68, 3 (2019), 2306–2315.

[13] S. Liu, F. Yang, W. Ding, X. Wang, and J. Song. 2016. Two-dimensional structured-compressed-sensing-based NBI cancelation exploiting spatial and temporal correlations in MIMO systems. *IEEE Trans. Veh. Technol.* 65, 11 (2016), 9020–9028.

[14] S. Liu, F. Yang, and J. Song. 2015. Narrowband interference cancelation based on priori aided compressive sensing for DTMB systems. *IEEE Trans. Broadcast.* 61, 1 (2015), 66–74.

[15] X. Ma, F. Yang, S. Liu, and J. Song. 2018. Channel estimation for wideband underwater visible light communication: A compressive sensing perspective. *Opt. Express* 26, 1 (2018), 311–321.

[16] C. A. Metzler, A. Maleki, and R. G. Baraniuk. 2016. From denoising to compressed sensing. *IEEE Trans. Inform. Theory* 62, 9 (2016), 5117–5144.

[17] C. A. Metzler, A. Mousavi, and R. G. Baraniuk. 2017. Learned D-AMP: Principled neural network based compressive image recovery. In *Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17)*. 1770–1781.

[18] E. Panayirci, H. Senol, M. Uysal, and H. V. Poor. 2016. Sparse channel estimation and equalization for OFDM-based underwater cooperative systems with amplify-and-forward relaying. *IEEE Trans. Signal Process.* 64, 1 (2016), 214–228.

[19] K. S. Priyanjali and A. V. Babu. 2014. An improved least square channel estimation technique for OFDM systems in sparse underwater acoustic channel. In *2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*. 2521–2525.

[20] P. Qarabaqi and M. Stojanovic. 2013. Statistical characterization and computationally efficient modeling of a class of underwater acoustic communication channels. *IEEE J. Ocean. Eng.* 38, 4 (2013), 701–717.

[21] S. Ramani, T. Blu, and M. Unser. 2008. Monte-Carlo sure: A black-box optimization of regularization parameters for general denoising algorithms. *IEEE Trans. Image Process.* 17, 9 (2008), 1540–1554.

[22] L. Wan, X. Qiang, L. Ma, Q. Song, and G. Qiao. 2019. Accurate and efficient path delay estimation in OMP based sparse channel estimation for OFDM with equispaced pilots. *IEEE Wireless Commun. Lett.* 8, 1 (2019), 117–120.

[23] J. Wang, Z. Yan, W. Shi, and X. Yang. 2019. Underwater acoustic sparse channel estimation based on DW-SACoSaMP reconstruction algorithm. *IEEE Commun. Lett.* 23, 11 (2019), 1985–1988.

[24] X. Wei, C. Hu, and L. Dai. 2021. Deep learning for beamspace channel estimation in millimeter-wave massive MIMO systems. *IEEE Trans. Commun.* 69, 1 (2021), 182–193.

[25] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang. 2017. Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising. *IEEE Trans. Image Process.* 26, 7 (2017), 3142–3155.

[26] Y. Zhang, H. Sun, F. Xu, and D. Wang. 2008. OFDM transform-domain channel estimation based on MMSE for underwater acoustic channels. In *2008 2nd International Conference on Anti-counterfeiting, Security and Identification (ASID)*. 177–181.

[27] S. Zhou and Z. Wang. 2014. *OFDM for underwater acoustic communications* (1st ed.). John Wiley & Sons, Ltd.