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Article

Optimal-HYPnet: Hybrid deep learning technique for jointly optimizes channel estimation and robust signal detector in OFDM system

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Abstract: In orthogonal frequency-division multiplexing (OFDM) systems, obtaining precise channel state information (CSI) is difficult. The number of antennas raises the pilot training and computing complexity of traditional channel estimation algorithms. Such inadequate characteristic makes the signal detection and channel estimation become challenging issues for the high-rate and reliable transmissions. Recently, several works have proposed for jointly optimized channel estimation and signal detector. Since the channel estimation performance might be degraded due to complex methodologies. This paper proposes a hybrid deep learning method for jointly optimizes channel estimation and signal detector(Optimal-HYPnet) which is used in 5G communication systems. First, we develop a reliable and scalable bi-directional convolutional neural network (Bi-CNN) to assess the channel in multipath circumstances. Then, develop an improved seagull optimization (ISO) algorithm to reduce the pilot overhead by using scheduling the pilot phase shifts optimally. Moreover, we illustrate a near-optimal buffer-aided LRT (NOLRT) detector to estimate channel information which is robust to the channel estimation error. Finally, we compare our proposed Optimal-HYPnet performance to existing approaches in terms of MSE and BER.
Keywords: OFDM, channel estimation, signal detector, pilot signal scheduling, Optimal-HYPnet, Information systems.

1. Introduction

High data speeds, reduced latency, increased capacity and enhanced QoS for existing wireless networks applications. Multipath delay spread and Doppler shift induce frequency selective fading. Frequency-selective fading and orthogonal frequency division multiplexing (OFDM) have become popular in recent years [1][2]. By converting frequency-dependent fading channels into frequency-independent fading channels, OFDM simplifies complicated equalisation and decoding. The OFDM technology reduces inter symbol interference (ISI) and increases capacity. The unpredictable and random characteristics of wireless channels may drastically influence communication quality, and key procedures like data demodulation need precise channel parameters. Channel estimation techniques for OFDM systems are blind and non-blind [3][4]. It uses the statistical behaviour of the incoming signals and requires a lot of data.

Non-blind channel estimation techniques use known data like pilot. OFDM is a widely utilized technology in broadband wireless communications that has gained popularity due to its potential to increase data rates across wireless channels. The research of OFDM is motivated by its simplicity and resistance to frequency selective channels. OFDM-MIMO [5] has a lot of potential for future wireless communications.

On-flight data modulation (OFDM) channel estimate and signal identification has been Traditional estimate techniques like least square and minimal mean square error (MMSE) are employed and improved [6]. Using second order channel statistics, MMSE estimate improves detection performance [7][8]. Deep learning (DL) is a useful approach for channel estimation and signal identification in wireless communication systems [13]. In an OFDM system, DL estimates channel and symbol sizes [9]. These networks have been effectively used in CSI-based localization, channel equalization, and channel decoding in communication systems [12]. [11]. More applications in communication systems are found as device computational resources improve and data becomes more readily available [12]. However, the number of parameters increases, necessitating a large volume of training data and a protracted training time [13]. Less understanding of DL approaches' fundamental mechanics restricts their improvement and expansion [14]. The DNN model predicts data transmission in various channel circumstances [15]. The DL system is initially trained offline using channel simulation data, and then used to recover live transmitted data. The DL-based strategy is also more resilient when fewer training pilots are utilized, cyclic prefix is deleted, and nonlinear clipping noise present. The tapped-delay line (TDL) channel model [16] improves performance and robustness of the DL technique. To learn DNN, you need to estimate the channel and compensate it [17].

OFDM classification shows improved reliability over the traditional technique [18]. To increase performance, a two-stage technique for combined OFDM channel estimation and signal identification is developed. A linear polynomial approximation models channel fluctuation during a symbol period [19]. Using the pilot signals, a close-form function is generated. Interference compensation and qSIS approaches are utilized to enhance estimation and detection. To convert pilot readings into preliminary values and monitor coarse variations, an ADD-TT is employed. The SR-ConvLSTM [20] monitors channel severe fluctuations by deriving temporal spectral correlation from data symbols.

Our contributions. For further enhancement in channel estimation and signal detector, a hybrid deep learning technique is proposed by using optimization algorithm (Optimal-HYPnet).

The proposed Optimal-HYPnet method major contributions are:

1. In multipath circumstances, a bi-directional convolutional neural network (Bi-CNN) is employed to estimate the channel.
2. An improved seagull optimization (ISO) algorithm utilized to reduce the pilot overhead by using scheduling the pilot phase shifts optimally.
3. A near-optimal buffer-aided LRT (NOLRT) detector estimates the channel information which is robust to the channel estimation error.
4. Finally, we compare our proposed Optimal-HYPnet performance to existing approaches in terms of MSE and BER.

The article’s remaining sections are: Recent work on OFDM channel estimation and signal detector optimization is described in Section 2.Section 3 portrays the proposed Optimal-issue HYPnet's approach and system design. The working function of the proposed Optimal-HYPnet for OFDM systems is presented in Section 4. Section 5 discusses simulation results, andSection 6 summarizes the research.

2. Literature review

Around the world, researchers have been studying how to combine machine and deep learning to enhance channel estimates and signal detection in OFDM systems. Table 1 illustrates and tabulates the literature in several areas.

Qing et al. [21] developed an MM-OFDM-IM detector based on the EM method to increase detection performance. The aim was to find the most probable mode permutation and related signal constellation points by reducing the Euclidean distance. Monte Carlo simulations had validated the EM detector's BER performance.

For carrier frequency offset, sampling time offset, and channel impulse response, Baghaki et al. [22]. It assumed Gaussian noise and random input. Derived from neighbouring pilot, non-pilot, and noise. It applied the Cramer-Rao restriction to unbiased joint parameter estimators.

For MIMO-OFDM, Cheng et al. [23] developed a joint time-variant CFO and frequency-selective channel response estimation technique. The joint estimator is based on maximum probability.

Blind channel estimation approach for amplify-and-forward (AF) two-way relay network (TWRN) with two terminal nodes and one relay node suggested by Lin et al. [24]. Frequency selective channels employed OFDM modulation. They examined cyclic prefix and zero padding. The proposed power reduction approach estimated the cascaded channel causing self-interference to compute the estimated Cramer-Rao limits using theoretical mean square error.

Ye et al. [25] examined two problematic block fading large MIMO networks. The first alternative would be to have an effective uplink channel estimation technique that reduces or eliminates pilot contamination. Other tasks included decoding multiuser data blocks in groups. Both joint multiuser channel estimation and data block detection were 2D sparse signal reconstruction problems, with joint channel estimation being the more complex. The 2D-SL0-SD data decoding algorithm used sparse representation in restricted alphabet set for each transmitted data signal.

Raul et al. [26] have proposed Taylor-least square error method (TLSE) is used to enhance the MIMO-OFDM system performance. The channel estimation is accomplished by using unique optimization technique which developed by combining LSE with the Taylor series. TLSE and DRO (QAM) excelled witha0.0001 minimum BER, and a 0.9965 maximum throughput.

Li et al. [27] have proposed OFDM frame is more efficient and differential correlation technique is possible to remove the interference produced by CFO. The PN sequence retrieves the partial common support (PCS) information for every channel. CS reconstruction approach is used for the PCS information as a priori knowledge which used to estimate the correct channel more accurately. The capacity of this system is used to resist CFO attacks and independence from channel sparsity level is two of its most significant advantages.

To deliver higher performance, Amran et al. [28] designed DL based LiFi communication algorithms that efficiently understand the distinguishing features and user behaviour. The conditional hotspot model analyzed a realistic LiFi channel with random device orientation and obstruction. DL-based approaches outperformed LS/MMSE-based channel estimation algorithms in more realistic and complicated indoor environments.

Table 1 Summary of Research Gap

Ref.	Methodology	Detector	Findings	Remarks
[21]	Signal detection, index modulation	Expectation maximization	Achieve better BER, MSE	Affected by the frequency selective fading effects
[22]	Frequency, time offset, and channel estimation	Maximum-likelihood	Achieve better BER, RMSE	Huge multi-path propagation
[23]	Frequency offset, channel estimation	Maximum-likelihood based grid search	Achieve better BER, MSE	Mutual interference by sharing the same resources
[24]	Blindchannel estimation	AF and TWRN	Achieve better BER, MSE	Complex design to get CSI
[25]	Channel estimation, signal block detection	2D-SL0-SD, MPSK	Achieve better BER, MSE	Relatively high channelestimation errors

[26]	Channel estimation	TLSE, DRO and STBC	Achieve better BER, MSE	High computational complexity
[27]	Frequency offset, channel estimation	Compressed sensing	Achieve better BER, MSE	Difficult to obtain coherence time
[28]	Signal detection, resource allocation	Deep learning detector	Achieve better BER, MSE	CSI estimation as typical time series learning problem
[29]	Activity detection, channel estimation	Turbo message passing algorithm	Achieve better BER, MSE	Not able to pursue estimation from random signals
[30]	Channel estimation, data detection	Support vector machine (SVM)	Achieve better BER, MSE	Not suitable for multi-path channel models

For massive machine-type communication (mMTC), Jiang [29] developed grant-free non-orthogonal multiple access system. The correlation of OFDM subcarrier frequency responses using a block-wise linear channel model. The frequency-selective channel was estimated using a linear function with just two variables for every continuous OFDM subcarrier. There were fewer variables and sub-blocks needed to effectively balance for channel frequency selectivity.

In massive MIMO systems with one-bit ADCs, Nguyen et al. [30] suggested using Support Vector Machine (SVM) for effective and reliable channel estimation and data detection.SVM was implemented in the first step of a two-stage detection technique. When the channel was known, the data detection approach performed extremely close to Maximum Likelihood (ML) detection. Combining decoded and pilot data vectors with SVM improved estimation and detection performance.

3. Problem Methodology and System architecture

3.1 Problem Methodology

Deep learning is proposed for channel estimation and signal detection in end-to-end OFDM systems [31]. In order to detect/recover transmitted symbols, one must first estimate CSI explicitly. An offline simulation of channel statistics is utilised to build a deep learning model that is subsequently used to retrieve the online transmitted data. Based on simulation results, deep learning-based technique recognises transmitted symbols and addresses channel distortion. These approaches have lately gained popularity in academia and business for applications such as radio resource allocation, physical security, signal decoding and channel estimation. Researchers didn't consider Doppler frequencies, which cause considerable variations in channels over time and render them non-stationary. Between the training and testing phases of a DNN model, the receiver's velocity might fluctuate greatly. Those learning approaches outperformed the traditional suboptimal channel estimating methods by learning and predicting the connection between the different realizations of the propagation channels. A proper estimation of channel is needed for performing this efficiently as measure for receivers. The popular LS or MMSE estimator is not proficient. Such computational complexity is very high when the channel estimation is applied to OFDM systems making a poor choice of mobile devices. Solving issues of the real world problems is a challenging taskand the joint optimization technique is used to find solutions. Therefore such issues may be sorted out using trial and error method with many such techniques of optimization. The Optimal-HYPnetis proposed to solve above gathered research gaps.

The proposed work major contributions are:

1. To limit the impact of ISI in transmitter/receivers to convey digital signals with lowest error rate.
2. To concentrate jointly optimizes channel estimation and robust signal detector in OFDM system
3. To introduce hybrid deep learning method to estimate the channel in OFDM system with different multipath scenarios.
4. To develop an optimization algorithm to reduce the pilot overhead and MSE by optimal pilot phase shifts scheduling.
5. To propose the robust signal detector to detect CSI to improve the receiver data detection performance.

3.2 System architecture of proposed Optimal-HYPnet

Fig. 1 depicts the OFDM system architecture with Optimal-HYPnet-based channel estimation and signal detection. The baseband OFDM system is conventional. A parallel data stream is generated on the transmitter side, andthe IDFT is used to transform signals from frequency to time domain. Then a cyclic prefix (CP) reduces inter-symbol interference (ISI).The CP length should not be shorter than the channel's maximum delay spread.

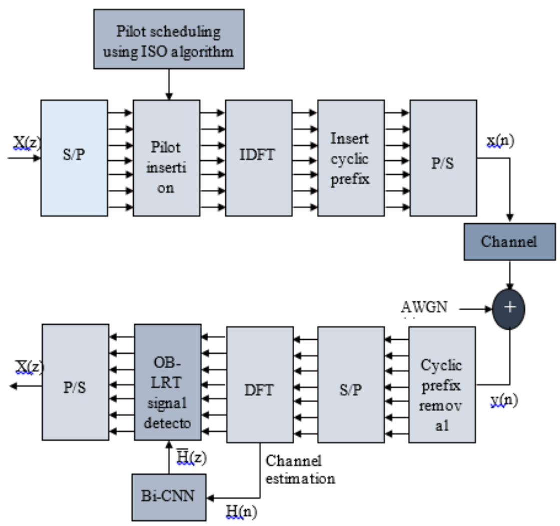

Fig. 1 System model of our proposed Optimal-HYPnet for OFDM system

A multi-path channel with complex random variables. In this case, the received signal $y(n)$ is

$$y(n) = x(n) \otimes H(n) + AWGN(n) \tag{1}$$

where $\otimes$implies the circular convolution whereas $x(n)$and $AWGN(n)$mean the transmitted signal and the additive white Gaussian noise (AWGN), respectively. After eliminating the CP and DFT, the obtained frequency domain signal $\overline{X}(z)$represents:

$$\overline{X}(z) = x(z) \otimes \overline{H}(z) + AWGN(z) \tag{2}$$

The pilot symbols are in the first OFDM block, whereas the transmitted data is in the subsequent OFDM blocks. Channels that span the pilot and data blocks may be viewed as constants that change across frames.

4. Proposed methodology

This section demonstrates the working function of proposed our Optimal-HYPnet for OFDM as follows: First, we explain the process of optimal pilot scheduling using ISO algorithm, then the channel estimation is describe in bi-directional convolutional neural network (Bi-CNN). Finally, the working process of the near-optimal buffer-aided LRT (OB-LRT) signal detector is described with the proper mathematical model.

4.1 Improved seagull optimization (ISO) algorithm

Reducing the pilot contamination in OFDM is one of the demanding and essential tasks in recent days. Because, pilot contamination affects the overall performance of communication system, so it must be reduced for enabling a reliable data transmission. Energy harvesting is important considerations in OFDM systems, which improves the communication efficiency of transmit and receive antennas. For this reason, different pilot scheduling mechanisms are developed in the traditional works, which intends to develop the pilot reuse mechanism to reduce contamination effects. Still, it remains with the issues like increased channel estimation error, complexity and reduced performance rate. In this study, we utilized an improved seagull optimization (ISO) algorithm for pilot sequence scheduling which optimizes the pilot contamination to solve overhead. Researchers say seagulls are smarter; in order to attract the worms to the surface, they emit sounds like rain with their feet. Although most animals do not drink clean, salty water, seagulls do. Seagull and migration patterns are their most significant characteristic features. Seagulls employ cyclical migrations to find abundant sources of food. In the optimization problem, clouds migrate using the following equation.

$$\vec{c}_t = B \times \vec{q}_t(y) \tag{3}$$

$$B = F_c - \left(y \times \left(\frac{F_c}{Max_{iteration}} \right) \right) \tag{4}$$

where $\vec{c}_t$ implies seagull final location, $\vec{q}_t(y)$ symbolizes seagull current location, y implies current iteration number, F_c represents control parameter, and $Max_{iteration}$ be maximum number of iterations. The seagulls then fly for their best neighbour:

$$\vec{m}_t = B \times (\vec{q}_{at}(y) - \vec{q}_t(y)) \tag{5}$$

where $\vec{m}_t$ indicates seagull location in relation to the best seagull, $\vec{q}_{at}(y)$ signifies the best seagull position, and A be balancing parameter. The A parameter balances exploration and exploitation:

$$A = 2B^2 \times R \tag{6}$$

where R is random number and the location of the best solution as follows:

$$\vec{d}_t = | \vec{c}_t + \vec{m}_t | \tag{7}$$

where $\vec{d}_t$ is the distance between the box and the corresponding box. As the optimal solution move, they change the angle and speed of the attack. The seagull uses a spiral motion to attack:

$$y' = R \times \cos K \tag{8}$$

$$x' = R \times \sin K \tag{9}$$

$$z' = R \times K \tag{10}$$

$$R = u \times e^{Kv} \tag{11}$$

where R denotes vortex rotation radius, K means random number, u, v are constant coefficients determining the rotational motion, e implies the natural loop basis. The seams updated position after rotation is as follows:

$$\vec{q}_t = (\vec{d}_t \times y' \times x' \times z') + \vec{q}_{at}(y) \tag{12}$$

Pseudo code 1 describes the working function of pilot sequence scheduling using improved seagull optimization (ISO) algorithm.

Pseudocode-1 Pilot sequence scheduling using ISO

Input : initialize input pilots, thresholds and $\vec{q}_t(y)$

Output : pilot signal scheduling

Initialize the initial population randomly;

The SOA employs the A variable to avoid collision $\vec{c}_t = B \times \vec{q}_t(y)$

If i=0

Update position of the current whale by $B = F_c - \left(y \times \left(\frac{F_c}{Max_{iteration}} \right) \right)$

Seagulls move towards the direction of best neighbour $\vec{m}_t = B \times (\vec{q}_{at}(y) - \vec{q}_t(y))$

Select a random seagulls change, $\vec{d}_t = |\vec{c}_t + \vec{m}_t|$

End if

Updated location of seagulls after spiral movement $\vec{q}_t = (\vec{d}_t \times y' \times x' \times z') + \vec{q}_{at}(y)$

End

4.2 Optimal channel estimation using bi-directional CNN

In OFDM system, for second-hop channel estimation, the source pilot symbols are FDM multiplexed with the cooperative data stream. No data rate loss for additional pilot subcarriers but unclear cooperative data interference. The bi-directional convolutional neural network (Bi-CNN) is widely used in various fields due to its ability to extract proven robust features. Thus, the confluence layers are multi-layered. Because of the original sequence's complex non-linear mapping connection, this causes considerable error collection, affecting the network prediction accuracy. Since it is impossible to fully capture information using a Bi-CNN, multi-dimensional convolutional layers are designed to pre-filter the original array and then extract different sized functions into the Bi-CNN as input to improve the Bi-CNN network computational efficiency and minimizes BER. The multi-dimensional confusion layer is compute as follows:

$$Z_K = F_1(w_K * x_j + a_K) \tag{13}$$

where Z_K signifies the output of convolutional layer at numerous scales. ‘ x_j ’ represents the time arrangement as input. The network has K layers. Filters w_K and biases a_K are conforming to kernels. ∗means convolutional operation. ‘ F_1 ’ implies the ReLU activation meaning, and its appearance is as

$$b_K = F_1(Z_K(x_j) = \max\{0,\ Z_K(x_j)\} \tag{14}$$

where b_K is the importance of implementation $Z_K(x_j)$. Bi-CNN is designed to completely remove hidden information. The final output of the Bi-CNN module describes as follows.

$$\overrightarrow{g}_K = \sigma(w^{(F)} Z_K + w^{(F)} \overrightarrow{g}_{K-1} + a^{(F)}) \tag{15}$$

$$\overleftarrow{g}_K = \sigma(w^{(a)} Z_K + w^{(a)} \overleftarrow{g}_{K-1} + a^{(a)}) \tag{16}$$

$$\vec{g}_K = h(F_2[\vec{g}(Z_K), + \vec{g}(Z_K)]) \tag{17}$$

where indicates $\vec{g}_K$ Bi-CNN output with different inputs. → indicates positive, and ← indicates reverse. F_2 implies Tanh beginning function. Each Bi-output CNN's value is calculated using a designed gate attention method, which then returns the optimal predicted value as an input. The gate attention combines the Softmax function to calculate the value of the focus at different levels of the projection as follows:

$$o_K = \sum_j \omega_0 \overline{g}_{j,K} + a_0 \tag{18}$$

$$q_K = \begin{bmatrix} q(\overline{g_j = 1 \mid o_1}) \\ q(\overline{g_j = 2 \mid o_2}) \\ \vdots \\ q(\overline{g_j = K \mid o_K}) \end{bmatrix} = \frac{1}{\sum_{i=1}^{K} E^{0_i^S \overline{g}_j}} \begin{bmatrix} E^{0_1^S \overline{g}_j} \\ E^{0_2^S \overline{g}_j} \\ \vdots \\ E^{0_K^S \overline{g}_j} \end{bmatrix} \tag{19}$$

Softmax defines the additional dependency and weight parameters of the function a_0 and ω_0 respectively. j signifies the data arraylength. K stands for number of scales. Gate q_K focus parameter for all predicted value. Therefore, the optimal estimated value G as follows:

$$G = C_{attention}([q_1 \cdot \overline{g}_1] \oplus [q_2 \cdot \overline{g}_2] ... \oplus [q_K \cdot \overline{g}_K]) \tag{20}$$

where $C_{attention}(\cdot)$ and $\oplus$epitomize the fusion operation. A convolution block has convolution and average pooling layers.The medium coupling action will weaken the range of abnormal peak points, and small curve action suppresses the noise, which better reflects the operating condition of the equipment. In Bi-CNN, the smoothed and de-noised layer is describes as follows:

$$p_j = F_1(w_j * G_j + a_j) \tag{21}$$

$$t_j^i = avg\,(p_j^i, ...p_j^J) \tag{22}$$

Thus, the regression layer has numerous complete connection layers as follows.

$$r = F_2(w_F \cdot flatten(t_j) + a_F) \tag{23}$$

where r signifies the final predictive value. w_F represents the weight parameters, though a_F is the additional bias. $flatten(\cdot)$ embodies flatten operation. The loss function l_2 is designed by minimum MSE function which is describes as follows:

$$l_2 = \arg\min \sum_{j=1}^{m} (r - \hat{r})^2 \tag{24}$$

Here $\hat{r}$ means actual value and M indicates prediction sequencelength. Two conventional layers are proposed in this research, an intermediate layer, Bi-CNN layers, and output layer. The pseudo code 2 represents the working process of optimal channel estimation using Bi-CNN algorithm.

Pseudocode-2 Optimal channel estimation using Bi-CNN	
Input : y(n) and H(n)	
Output : optimal H matrix $\overline{H}(z)$	
1	Initialize the net parameters
2	Convert the format of input data:
3	ReLU activation function $b_K = F_1(Z_K(x_j) = \max\{0, Z_K(x_j)\}$
4	For i=t to 1
5	The smoothed and de-noised layer $p_j = F_1(w_j * G_j + a_j)$

6	Multiple full connectional layers $r = F_2(w_F \cdot flatten(t_j) + a_F)$
7	Define MSE $l_2 = \arg\min \sum_{j=1}^{m} (r - \hat{r})^2$
8	End

4.3 Signal detector using near-optimal buffer-aided LRT (NO-LRT) detector

In this study, we explore two forms of periodic pilots with varying time periods. Use of periodic pilots in weak OFDM transmissions is proposed for accurate spectrum sensing. Assuming that the secondary users (SU) signal is completely synced with the primary users (PU) signal, we first design a near optimal LRT detector (NOLRT). The test statistic is calculated by NO-LRT detector using locally produced pilots and received signal samples. With LRT detectors, we may examine their performance across multipath fading channels. i = 1, g(0) = 1 and $\tau_0 = 0$, and over AWGN channel.

$$R(N) = \begin{cases} \omega(N), & H_0, \\ a(N) + \omega(N), & H_1 \end{cases} \tag{25}$$

The SU received a signal that is as follows:

$$F(R(N) \mid H_0) \frac{1}{\pi\sigma_\omega^2} \exp\left(-\frac{|R(N)|^2}{\sigma_\omega^2} \right) \tag{26}$$

The SU's signal under the hypothesisof H_1 is $R(N) = a(N) + \omega(N)$.

We describe $q(N) = u(N) + v(N)$.

Accordingly, the PDF of $R(N) \mid H_1$ is define as follows:

$$F(R(N) \mid H_1) \frac{1}{\pi(\sigma_\omega^2 + \sigma_t^2)} \exp\left(-\frac{|R(N)| - q(N)|^2}{\sigma_\omega^2 + \sigma_t^2} \right) \tag{27}$$

Under the hypothesis H_1, we state a 2 × 1 random vector $R(N) = [R(N), R(N+n)]^S$. A symbol's CP is intended to absorb path delay, so the initial sampling time instant n should be inside the CP of an OFDM symbol. Assuming thi, $R(N)$ is a CPsample, where $R(N+n)$ implies data block copy. So $R(N)$ is two highly correlated signal samples. Hence, $R(N) \mid H_1$ PDF expressed as

$$F(R(N) \mid H_1) \frac{1}{\pi^2 \det(r)} \exp\left(-r^H(N) r^{-1} r(N) \right), \tag{28}$$

where $r(N) = R(N) - e[R(N)]; r^G(N)$ implies conjugate transposition of r(N); r means $R(N) \mid H_1$ covariance matrix, which is defined as $r = eR(N) r^G(N)$; det(r) indicates r determinant. Subsequently $R(N) = a(N) + \omega(N)$ and $a(N)$ in the CP is copy of $a(N+n)$ in the equivalent data block as follows:

$$e[R(N)] = [q(N), q(N)]^S \tag{29}$$

$$e[R(N)R^H(N)] = \begin{bmatrix} \sum_q^1(N) & \sum_q^2(N) \\ \sum_q^2(N) & \sum_q^1(N) \end{bmatrix}, \tag{30}$$

$$e[R(N)]e[R^H(N)] = \begin{bmatrix} |q(N)|^2 & |q(N)|^2 \\ |q(N)|^2 & |q(N)|^2 \end{bmatrix}, \tag{31}$$

The r matrix is simplified as $r = e[R(N)R^G(N)] - e[R(N)]e[R^G(N)]$.

$$r^{-1} = \frac{1}{\det(r)} \begin{bmatrix} \sigma_t^2 + \sigma_\omega^2 & -\sigma_t^2 \\ \sigma_t^2 & \sigma_t^2 + \sigma_\omega^2 \end{bmatrix} \tag{32}$$

$$r^H(N)r^{-1}r(N) = \frac{\sum_\Delta(N) - 2\rho\prod_\Delta(N)}{(\sigma_t^2 + \sigma_\omega^2)(1-\rho^2)} \tag{33}$$

PDF of $R(N)\,|\,H_1$ can be represented as

$$F(R(N)\,|\,H_1) = \frac{1}{C_1}\exp\left(-\frac{\sum_\Delta(N) - 2\rho\prod_\Delta(N)}{(\sigma_t^2 + \sigma_\omega^2)(1-\rho^2)}\right) \tag{34}$$

where $C_1 = \pi^2\left[\left(\sigma_t^2 + \sigma_\omega^2\right) - \sigma_\omega^4\right]$ be constant. The probability ratio function for N in an OFDM symbol is:

$$\Lambda = \frac{F(R(N),\cdots,R(N+m-1)\,|\,H_1)}{F(R(N),\cdots,R(N+m-1)\,|\,H_0)} \tag{35}$$

According to H_0 hypothesis, the SU only receives complex AWGN.Thus, the joint PDF Jr (H_0) of $R(N),\cdots,R(N+m-1)\,|\,H_0$ written as follows:

$$j_R(H_0) = \prod_{M=N}^{N+m-1} F(R(M)\,|\,H_0) \tag{36}$$

Contrarily, in H1, the SU gets both complex AWGN and OFDM signals with periodic pilots. Because is periodic and predictable, it is influenced by the PU's transmission power.

$$\sum_{M=N}^{N+M-1} re\left\{R(M)q^*(M)\right\}\Lambda \underset{H_0}{\overset{H_1}{\gtrless}} 1/2\ \Lambda_\chi \tag{37}$$

With periodic pilot, NOLRT detector for spectrum detection of very weak OFDM transmissions:

$$\mathrm{T}nolrt = \sum_{M=N}^{N+M-1} re\left\{R(M)q^*(M)\right\} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda nolrt \tag{38}$$

That is, the received signal sample should match the NOLRT detector's produced pilot. Time synchronization takes time and is unreliable in low SNR environments.

$$\frac{\partial \ln L}{\partial q(N)} = \frac{1}{\sigma_t^2 + \sigma_\omega^2} \sum_{L=0, L \ \mathrm{mod} \ K=0}^{L-1} \Delta^*(L, N) \tag{39}$$

We attain the maximum $q(m)$ probability estimation as

$$\hat{q}(N) = \frac{1}{[l/K]} \sum_{L=0, L \ \mathrm{mod} \ K=0}^{L-1} R(N - Lm) \tag{40}$$

Therefore, $\hat{q}^*(M)$ means unbiased and $q(m)$ consistent estimation. By substituting $q(m)$ with $\hat{q}^*(M)$, the proposed NOLRT detector describes as follows:

$$\mathrm{T}balrt = \sum_{M=N}^{N+M-1} re\{R(M)\hat{q}^*(M)\} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda balrt \tag{41}$$

where T_{balrt} and λ_{balrt} is the test statistic and decision threshold. The 'balrt' detector needs no time synchronization information and simple buffer cost. Pseudocode-3 describes the working process of NOLRT signal detector.

Pseudocode-3 NOLRT signal detector.	
Input : $R(N) = \omega(N)$ parameters	
Output : T_{balrt} and λ_{balrt}	
1	Initialize the H parameters
2	Predicted state vector and covariance;
3	the SU under the hypothesis $R(N) = a(N) + \omega(N)$
4	PDF of $R(N) \mid H_1$ define as $F(R(N) \mid H_1) \dfrac{1}{\pi^2 \det(r)} \exp\left(-r^H(N) r^{-1} r(N)\right),$
5	For j=0 Do
6	While q is not empty;
7	Define matrix r as $r^H(N) r^{-1} r(N) = \dfrac{\sum_\Delta (N) - 2\rho \prod_\Delta (N)}{(\sigma_t^2 + \sigma_\omega^2)(1-\rho^2)}$
8	Define likelihood ratio function $\Lambda = \dfrac{F(R(N), \cdots, R(N+m-1) \mid H_1)}{F(R(N), \cdots, R(N+m-1) \mid H_0)}$
9	End for
10	return dist[], previous
11	Transmission power of the PU $\sum_{M=N}^{N+M-1} re\{R(M) q^*(M)\} \Lambda \underset{H_0}{\overset{H_1}{\gtrless}} 1/2 \ \Lambda_\chi$
12	To estimate maximum likelihood $q(m)$ as $\hat{q}(N) = \dfrac{1}{[l/K]} \sum_{L=0, L \ \mathrm{mod} \ K=0}^{L-1} R(N - Lm)$
13	End

5. Results and Discussion

5.1 Simulation setup

This section evaluates and validates the proposed Optimal-HYPnet model performance using different simulation setup. Our proposed optimal-HYPnet model is compared to existing techniques in terms of bit-error rates (BERs) at various signal-to-noise ratios (SNRs). Minimal training pilots, no CP, or nonlinear clipping noise are utilized to test the Optimal-HYPnet model's robustness against other state-of-the-art models. Our tests use an OFDM system with 64 sub-carriers and a 16-length CP. The wireless channel uses the Wireless World Initiative's New Radio Model, with a 2.6GHz carrier frequency, 24 paths, and a maximum delay of 16. The modulation mechanism is QPSK.

5.2 Comparative analysis

When 8 pilot sequences used for channel estimation in each frame, BER of proposed optimal-HYPnet model is 97.333%, 92% and 60% efficient than the LS, MMSE and deep learning models respectively for SNR=5dB; BER of proposed optimal-HYPnet model is 97.6%, 92.5% and 25% efficient than the LS, MMSE and deep learning models respectively for SNR=10dB; BER of proposed optimal-HYPnet model is 98.636%, 94% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=15dB; BER of proposed optimal-HYPnet model is 99.524%, 97.5% and 66.667% efficient than the LS, MMSE and deep learning models respectively for SNR=20dB; and BER of proposed optimal-HYPnet model is 99.773%, 98.75% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=25dB. The average BER of proposed optimal-HYPnet model is 98.458%, 94.032% and 51.316% robust than the LS, MMSE and deep learning models respectively. In each frame, Figure 2 illustrates the BER performance of 8 pilot sequences utilized for channel estimation.

When 64 pilot sequences used for channel estimation in every frame, proposed optimal-HYPnet model BER is 97.5%, 93.75% and 83.333% efficient than the LS, MMSE and deep learning models respectively for SNR=5dB; BER of proposed optimal-HYPnet model is 97.5%, 93.333% and 80% efficient than the LS, MMSE and deep learning models respectively for SNR=10dB; BER of proposed optimal-HYPnet model is 98%, 90% and 80% efficient than the LS, MMSE and deep learning models respectively for SNR=15dB. BER of proposed optimal-HYPnet model is 97.667%, 90% and 65% efficient than the LS, MMSE and deep learning models respectively for SNR=20dB; and BER of proposed optimal-HYPnet model is 97.5%, 90% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=25dB. The average BER of proposed optimal-HYPnet model is 97.579%, 93.03% and 80.833% robust than the LS, MMSE and deep learning models respectively. Fig. 3 shows the comparative analysis of BER performance for 64 pilot sequences used for channel estimation in every frame.

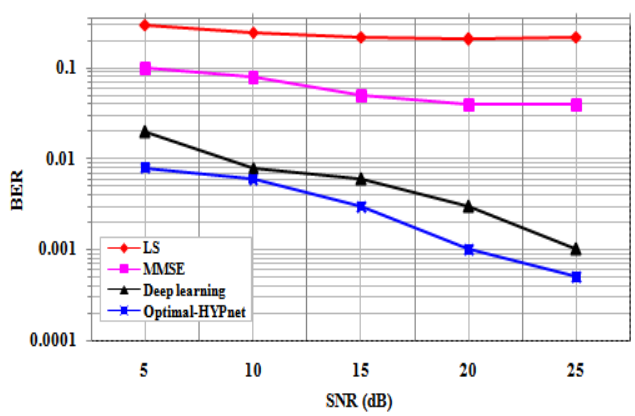

Fig. 2 BER performance for 8 pilot sequences used for channel estimation

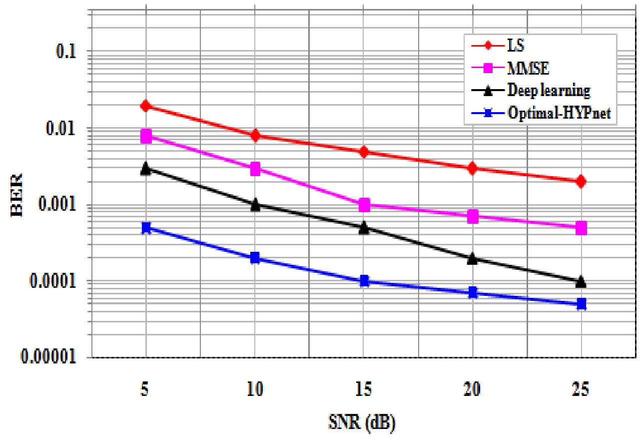

Fig. 3 BER performance for 64 pilot sequences used for channel estimation

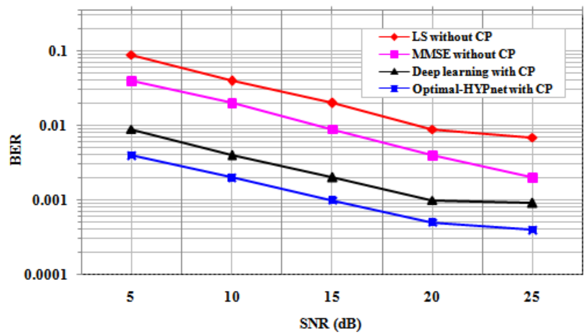

Fig. 4 BER performance with CPimpact

The CP transforms the physical channel's linear convolution into circular convolution, eliminating ISI. But transmission takes time and energy. This experiment will test the CP remover's performance. The BER of proposed optimal-HYPnet model is 95.556%, 90% and 55.556% efficient than the LS, MMSE and deep learning models respectively for SNR=5dB; BER of proposed optimal-HYPnet model is 95%, 90% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=10dB; BER of proposed optimal-HYPnet model is 95%, 88.889% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=15dB; BER of proposed optimal-HYPnet model is 94.444%, 87.5% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=20dB; and BER of proposed optimal-HYPnet model is 94.286%, 80% and 55.556% efficient than the LS, MMSE and deep learning models respectively for SNR=25dB. The average BER of proposed optimal-HYPnet model is 95.241%, 89.467% and 53.254% robust than the LS, MMSE and deep learning models respectively. Figure 4 compares BER performance with CP impact. The OFDM's high peak-to-average power ratio (PAPR) is a noteworthy flaw. Clipping and filtering is a simple and efficient way to minimize PAPR. Though, clipping produces nonlinear noise that may decrease estimation and detection performances.

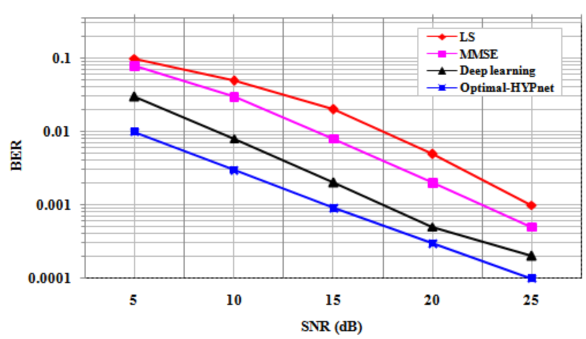

Fig. 5 BER performance without noise (ideal condition)

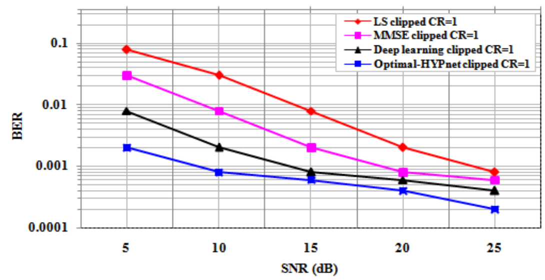

Fig. 6 BER performance with clipping noise

For without noise (i.e. ideal condition), BER of proposed optimal-HYPnet model is 90%, 87.5% and 66.667% efficient than the LS, MMSE and deep learning models respectively for SNR=5dB; BER of proposed optimal-HYPnet model is 94%, 90% and 62.5% efficient than LS, MMSE and deep learning models respectively for SNR=10dB; BER of proposed optimal-HYPnet model is 95.5%, 88.75% and 55% efficient than the LS, MMSE and deep learning models respectively for SNR=15dB; BER of proposed optimal-HYPnet model is 94%, 85% and 40% efficient than the LS, MMSE and deep learning models respectively for SNR=20dB; and BER of proposed optimal-HYPnet model is 90%, 80% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=25dB. The average BER of proposed optimal-HYPnet model is 91.875%, 88.133% and 64.865% robust than the LS, MMSE and deep learning models respectively. Fig. 5 illustrates the BER performance comparative analysis for the without noise in channel.

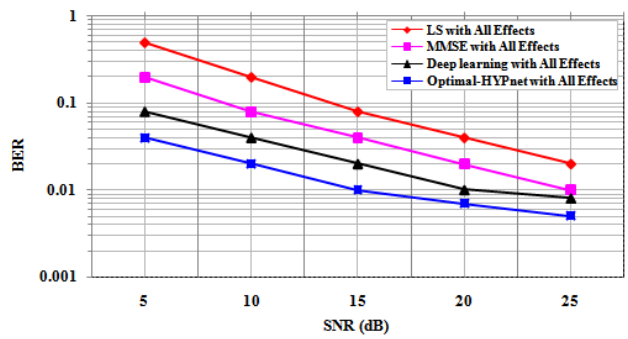

Fig. 7 BER performance with just 8 pilots, no CP, and clipping noiseoccurred

When clipping noise occurred in channel, BER of proposed optimal-HYPnet model is 97.5%, 93.333% and 75% efficient than the LS, MMSE and deep learning models respectively for SNR=5dB; BER of proposed optimal-HYPnet model is 97.333%, 90% and 60% efficient than LS, MMSE and deep learning models respectively for SNR=10dB; BER of proposed optimal-HYPnet model is 92.5%, 70% and 25% efficient than the LS, MMSE and deep learning models respectively for SNR=15dB; BER of proposed optimal-HYPnet model is 80%, 50% and 33.333% efficient than the LS, MMSE and deep learning models respectively for SNR=20dB; and BER of proposed optimal-HYPnet model is 75%, 66.667% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=25dB. The average BER of proposed optimal-HYPnet model is 96.689%, 90.338% and 66.102% robust than the LS, MMSE and deep learning models respectively. Fig. 6 shows the comparative analysis of BER performance for 8 pilot sequences used for clipping noise occurred in channel.

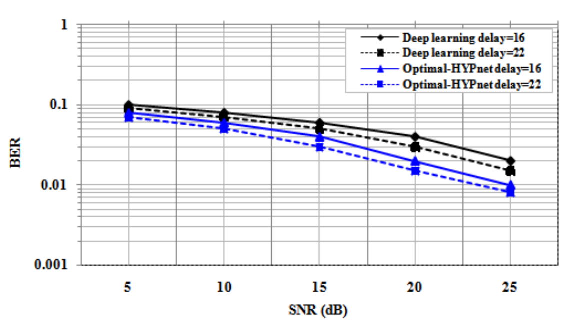

Fig. 8 BER performance with robustness Analysis

When all effects (8 pilots deployed, no CP, clipping noise occurred) occurred in channel, the BER of proposed optimal-HYPnet model is 92%, 80% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=5dB; BER of proposed optimal-HYPnet model is 90%, 75% and 50% efficient than LS, MMSE and deep learning models respectively for SNR=10dB; BER of proposed optimal-HYPnet model is 87.5%, 75% and 50% efficient than the LS, MMSE and deep learning models respectively for SNR=15dB; BER of proposed optimal-HYPnet model is 82.5%, 65% and 30% efficient than the LS, MMSE and deep learning models respectively for SNR=20dB; and BER of proposed optimal-HYPnet model is 75%, 50% and 37.5% efficient than the LS, MMSE and deep learning models respectively for SNR=25dB. The average BER of proposed optimal-HYPnet model is 90.238%, 76.571% and 48.101% robust than the LS, MMSE and deep learning models respectively. Fig. 7 shows comparative analysis of BER performance for all the effects occurred in channel. For the delay=16, the BER of proposed optimal-HYPnet model is perform very effective which is 37.5% and 28.571% robust than the existing deep learning model. Similarly, for the delay=22, the BER of proposed optimal-HYPnet model is perform very effective which is 42.333% and 32.157% robust than the existing deep learning model.

6. Conclusion

For joint optimization of channel estimation and signal detector, we propose a hybrid deep learning approach (Optimal-HYPnet).A bi-directional convolutional neural network (Bi-CNN) is used to calculate the channel in multipath circumstances which ensures reliability and scalability. An improved seagull optimization (ISO) algorithm is used to reduce the pilot overhead by using scheduling the pilot phase shifts optimally. A near-optimal buffer-aided LRT (NOLRT) detector is illustrated to estimate channel information which is robust to the channel estimation error.The simulation results demonstrate that our proposed Optimal-HYPnet outperforms existing channel estimation and detector.

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