A SURVEY ON DEEP LEARNING APPROACHES FOR CHANNEL ESTIMATION IN STOCHASTIC WIRELESS COMMUNICATION

M. Jyothsna (1) , Assistant Professor, P. Priyanka[2], M. Manvitha[3], M. Deevena[4], K. Alekhya[5]
Department of Electronics and Telematics Engineering, G.Narayanamma Institute of Technology and Science,Shaikpet,Hyderabad,India,

Abstract-A new non-parametric channel estimation algorithm for chaotic WPM system using pre-trained stacked denoising autoencoder based deep neural network. More importantly, by employing the ACF of the received signal, the method improves the estimation of channel parameters, and at the same time reduces MSE and BER. This improvement in the noise sensitivity is attributed by having both the ACF and SDAE because they offered a two tier protection to noise. This has the added advantage of not generating further probe signals to be transmitted, and hence reduces the bandwidth costs. Its performance is even superior in the above sense of the accuracy of channel estimation compared to conventional approach.

Keywords--Channel estimation, stacked denoising autoencoder (SDAE), deep neural network (DNN), chaotic base band wireless communication system (CBWCS).

I. INTRODUCTION

The wireless communication systems have advanced over the last few years but the most difficult problem that still persists is the determination of the impact cushion of the communication channel on the incoming signals. This difficulty is more complex in chaotic wireless communication since several criteria are involved and find it challenging to select suitable chaotic signals. Said signals, although complex, have tremendous benefits such as insulites to noise and use in conditions and climes over other kinds of signals. Hence for efficient communication, it is desirable to carry out a full channel estimation thereby ensuring the correct decoding of the received signals. Earlier, the methods used for channel estimation are Least Square (LS) and later advanced to Minimum Mean Square Error (MMSE). These methods depend on the fact that to the pilot signals along with the data are transmitted in order for the receiver to deduce the channel. But they waste valuable bandwidth, lower the data transmission rate to the end system and poorly perform under noisy conditions. To overcome these limitations, present research Scientists have proposed new methods including blind channel estimation, which does not include the pilot signal. An emerging and interesting channel estimation scenario is application of deep learning (DL) towards this purpose which is quite effective in wireless communication. The new channel estimation of the proposed deep-learning-based method for chaotic wireless communication systems is presented in this paper. The proposed approach learns the channel parameters by estimating the autocorrelation function (ACF) of the received chaotic signals and using a deep neural network (DNN) with stacked denoising autoencoder (SDAE) pre-learning, so it is pilotless. The method is claimed to reduce Mean Squared Error (MSE) of the estimate of the channel and so enhance estimation accuracy and system performance. Simulation outcome proves the concept of this approach can provide higher efficiency than the conventional techniques with reference to MSE as well as BER.

The journal paper titled “Analysis and Implementation of Channel Estimation in OFDM System Using Pilot Symbols” describes a technique that focuses at enhancing the methods adopted in channel estimation in Orthogonal frequency division multiplexing OFDM systems. It is now high time to accent on how the proposed and the existing techniques are built up on their limitations.Paper named “Channel Estimation Techniques in Wireless Communication” gives general over view estimating wireless communication channel and few mathematical models such as Channel Impulse Response (CIR). It discusses two key approaches: The Deep Belief Network (DBN), the traditional Maximum Likelihood Estimation (MLE) that employs pilot symbols to estimate the channel, and a comparatively realistic deep learning approach. The proposed deep learning approach improves low-resolution channel representations derived from MLE into high-resolution grids for higher accuracy. These techniques are used in equalization and demodulation in the emerging wireless systems such as MIMO and OFDM with the aim of reducing some degrading factors in signal transmission.The paper entitled “Deep Learning for Joint Channel Estimation and Signal Detection in OFDM Systems” describes deep learning based technique to improve the channel estimation and signal detection in OFDM. It introduces two neural networks: CENet to eliminate interpolation procedures for channel estimation, and a CCR Net to embed the estimated channel characteristics for transmission signal reconstruction. By adopting deep learning and analyzing time-frequency correlation of wireless fading channels, the proposed method achieves better performance as compared to the conventional methods such as Zero Forcing and Regularized Zero Forcing detectors. The channel estimation and equalization play critical role in wireless communication system, since it resolves problems of dynamic channel conditions of a wireless link. These conventional techniques, which include the Least Squares (LS) and Minimum Mean Square Error (MMSE) methods, are futile when it comes to rapidly changing environments, and are not flexible enough to handle nonlinear problems since they rely on deterministic channel estimation. While DCO techniques provide proactive and general solution to counteract channel impairments, deep learning techniques provides a more flexible solution where they use large amount of data to learn about various channel characteristics. The present work explores the use of deep learning techniques in channel estimation and equalization for the enhancement of wireless communication systems, something that could improve the performance of wireless communication systems impressively. For reliable data transmission in random wireless networks, channel estimation remains vital. Popular methods like LS and MMSE estimators have normally used pilot symbols or known training sequences, which results in low bandwidth utilization. First, they may not do well in mobile communications environments or in situations with a lot of noise; they yield quite low performance and high BER. On the other hand, our proposed approach using full deep learning relies on a trained DNN that was developed using SDAE, aims to estimate channel parameters from the received chaotic signal. This blind estimation reduces the workload for pilot sequences while achieving enhanced estimation in harsh conditions and saves bandwidth ICU. Deterministic chaos is much less amendable to noise and less flexible compared to the new approach where the DNN framework outperforms existing methods by using the inherent structure of chaotic signals.

II.TECHNIQUES

i.Existing Technique:

OFDM signal requires channel estimation to determine the effect on the transmitted data of the channel of communication. Traditionally, two primary channel estimation techniques are used: Least-Square (LS) Estimation: This method reduces the error between the received and the estimated signal because the estimation process is made easy. It is highly used due to the simplicity of the operation it is much sensitive to noise and interferences; therefore, it exhibits poor performance under harsh environments. Minimum Mean Square Error (MMSE) Estimation: This produces an improved channel usage for the enhancement of LS by including the channel statistical features. It is found to give a better result than the conventional approach of minimizing mean square error especially in a noisy environment. However, the computation of MMSE has made the problem more complexing and therefore not well suited for large systems.

The MLE technique is an ML method proposed where channel noise is described using the Gaussian probability distribution function and then adjusted to the signal data. Its main application area in wireless communication is to estimate the channel matrix H, which represents the effect of the wireless channel on the transmitted signal. As for MLE, it employs pilot symbols-Pk, which are the known transmitted signals, through which the receiver compares with the received signals aimed at channel estimation. This gives the receiver the Channel Impulse Response (CIR) enabling the receiver to combat noise, fading and distortion. Nonetheless, MLE entails a great deal of pilot symbols for estimation depriving it of high spectral efficiency, especially where wireless environment is changingly abrupt. However, for rapidly changing channels, as is common in high-mobility applications like vehicular communication that require the frequent transmission of pilots, MLE's performance degrades.

The technique currently used in the paper addresses the fundamental issues in OFDM based wireless communication such as channel estimation and detection of a signal requiring long time duration. Ref signals are incorporated in the transmitted data to estimate the channel at certain locations, and techniques of identification include LS and MMSE in determining coefficients of the channel. This is done at pilot positions and once the channel is estimated the full channel matrix can then be estimated using interpolation techniques such as linear inter-rep and Gaussian inter-rep. Following channel estimation, some detection procedures such as Zero Forcing (ZF) and Regularized Zero Forcing (RZF) are employed to endeavour at retrieving the transmitted signal given the current channel. But these techniques are normally in a lower performance because it cannot re-construct the correlation from the wireless channels for improving the channel estimation and signal recovery.

There are several conventional approaches to wireless channel estimation namely the Least Squares (LS) and Minimum Mean Square Error (MMSE) algorithms. The LS method determines channel parameters by minimizing the mean square error between the received signal and the estimated signal and as a result the LS approach is simple and not complicated to implement. It is excellent for low noise operation, for example with linear channels. Contrarily, the MMSE estimator uses priori information about the statistical properties of the channel and the received signals to reduce the error estimator. However, in spite of these benefits, both methods present inefficiencies especially in nonlinear, non-Gaussian noise channels and time variants channels. Because of such constraint, various enhancements in actual system performance are below par in complex wireless communication scenarios; thus, there is need to search for better options.

For reliable data transmission in random wireless networks, channel estimation remains vital. Popular methods like LS and MMSE estimators have normally used pilot symbols or known training sequences, which results in low bandwidth utilization. First, they may not do well in mobile communications environments or in situations with a lot of noise; they yield quite low performance and high BER. On the other hand, our proposed approach using full deep learning relies on a trained DNN that was developed using SDAE, aims to estimate channel parameters from the received chaotic signal. This blind estimation reduces the workload for pilot sequences while achieving enhanced estimation in harsh conditions and saves bandwidth ICU. Deterministic chaos is much less amendable to noise and less flexible compared to the new approach where the DNN framework outperforms existing methods by using the inherent structure of chaotic signals.

The paper introduces modifications to both LS and MMSE estimators to improve performance and reduce computational complexity: Modified MMSE Estimator: This variation takes advantage of the fact that the estimation matrix is large by sub- sampling it to the first L taps which are the most energy intensive of the channel. Thus, it avoids the complexity augmentation of estimation while achieving performance as close to the standard MMSE as possible. Modified LS Estimator: As with the modified MMSE, this technique gives an upper bound on how many taps we employ for estimation, which enables us to achieve better than the basic LS estimator's mean square error while incurring a reasonable computational load.

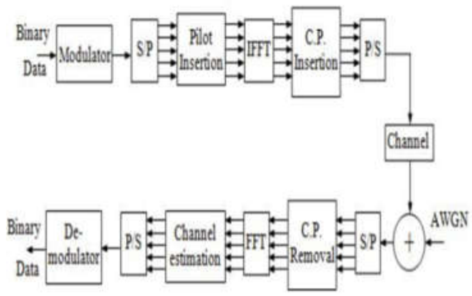


Fig. 2.1 Block diagram of OFDM system

The technique to infuse into the system, as described in the paper is called deep learning-based channel estimation that improves the conventional MLE. In this technique, the wireless channel response is considered in terms of a low rank and low dimensional time-frequency grid using MLE. This next grid is then passed through a Super-Resolution (SR) network that aims at enhancing the resolution of this grid and generating a high-resolution (HR) version of the channel response. The HR grid gives a more accurate estimation of the channel matrix H than the blind estimator Also, to increase the SNR and remove noise from the higher resolution image, an Image Restoration (IR) network is used, and then resulting channel is more accurate. This deep learning method reduces the dependence of the signal classification on the first large pilot symbol sets, and increases the accuracy of the channel estimation which makes the design ideal for fast-varying channel that would normally be difficult to estimate with traditional methods such as MLE.

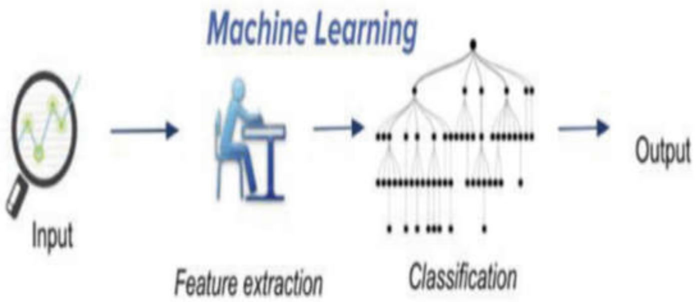


Fig. 2.2 Block Diagram of channel estimation in wireless communication

In the paper, a novel method for channel estimation and signal detection based on deep learning in OFDM systems is presented. It utilizes two main neural networks: Within this system, there are known as the Channel Estimation Network (CENET) and the Channel Conditioned Recovery Network (CCRNET). Different from the original interpolation schemes, CENET uses an image super-resolution approach to estimate the channel response since wireless fading channels exhibit time and frequency correlations. The output from CENET is then passed to the CCRNET which has been developed to de-convolute the transmitted signal off the estimated channel. This network requires GAN architecture to be implemented to allow it condition the transmitted signal from the data received. This performance analysis shows that integrating CENET and CCRNET yields superior performance compared with traditional techniques that directly estimate the channel and detect signals, as it provides improved accuracy and stability in response to differences in system parameters in practical application environments.

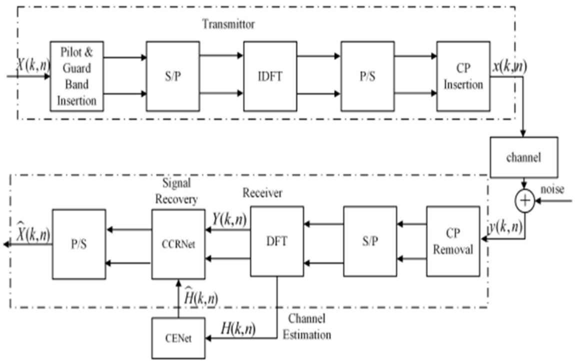
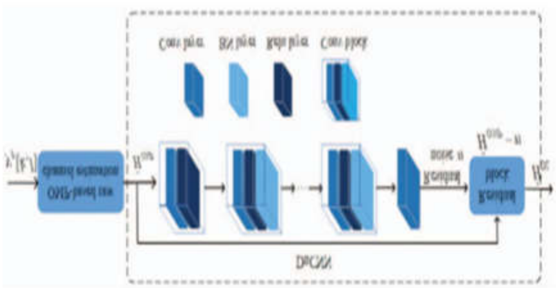


Fig. 2.3 DL-aided OFDM system architecture

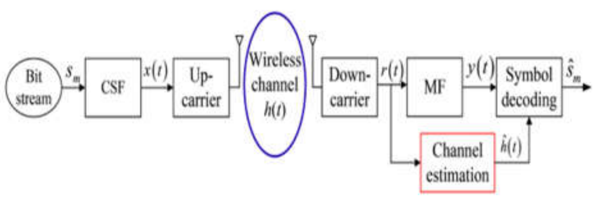
The proposed technique employs deep neural networks to enhance the channel estimation in the intervened wireless communication environment as follows. When training parameters of the ANNs, models like CNNs, and RNNs can train the non-linear characteristics and behaviours of chaotic signals. This is in contrast to other techniques that are unable to change in the same time frame to changing channel characteristics. I have also established that the deep learning approach is effective when there are several interferences with the quality of images and helps in narrowing down the margin of estimation errors. Moreover, it makes the process faster and so there is low latency time when transferring data from one location to another. The proposed technique, however, provides better results than simple methods such as LS and MMSE and better adaptability to new conditions. In a broad perspective, this use of deep learning will provide a significant advancement to enhance reliability and throughputs of future wireless communication systems.



Fig, 2.4 Block Diagram of DnCNN

ii.Proposed Technique:

However, the work that presents this solution employ a technique using deep learning with the Stacked Denoising Autoencoder (SDAE) for the blind channel estimation. Compared to transmit pilot symbols to train the decision, this method can learn the patterns from received interference signals, which has improved bandwidth efficiency greatly. More importantly, since the proposed method is based on the deep learning capability to estimate the channel conditions accurately, noise resistance and tunable to distinguish different channel variations help in giving better estimation. Further, the method successfully mitigate the bit error rates and being a solution to the challenges noted to have occurred in the conventional channel estimation approach. Last but not the least it presents a versatile solution for channel estimation in ARQ based noisy and jammed wireless channel environment.



Fig, 2.5 Block Diagram of CBWS

iii.Drawbacks:

The modifications that are proposed here result in a better performance of the LS and MMSE estimators. Simulations depict the variations in MSE by employing the generalized MMSE estimator and show that the current estimator performs well than the previously used LS and MMSE estimators for various SNR. Also, the present modification of the LS estimator shows improved performance over the basic LS technique, though at a little greater complexity. However, thus improving the situation, the computational load of the MLE and predominantly of the MMSE estimator increases as the size of the system grows. However, in large real-time applications, the reduction of the matrix size alleviates this problem, but establishing a trade-off between computational efficiency and estimation accuracy is still challenging.

The paper examines a number of limitations of the traditional MLE method for channel estimation. A major drawback of this approach is the high number of pilot symbols which results into high overhead and low Spectral efficiency especially when the channel profile is fading, a situation which places a lot of pressure on the systems resources and degrades the systems performance. However, the performance degrades in case of high mobility communication such as vehicular communication since it fails to adapt to rapid change in the channel conditions. Moreover, the idea of using deep learning exciting and useful in theory brings up questions about the actual training and execution of the model for real-time software. Still, as for the proposed improvements, the given approach is still promoted by rather serious barriers to be addressed for wide-spread adaptation in dynamic wireless environments.

The paper recognizes several limitations of the developed deep learning-based approach for joint channel estimation and signal detection in OFDM systems. Firstly, the requirement is a big amount of training data can be a problem since there can be a situation when it is possible to collect enough diverse data for training in the model. Besides, the complexity of the deep learning models will incur larger computational cost, which might be a problem for the real time implementation in the systems with limited resources. Finally, though the proposed method seems rather resistant, it may perform worse in vastly oscillating or unpredictable channel environments, and thus should be further enhanced.

Nevertheless, it is important to note notable drawbacks of the deep learning based channel estimation. It also calls for a great number of high-quality labeled data which may be costly and sometime hard to accquire. These models are complex which require much computational power and hence high energy consumption and slow throughput. Furthermore, it is hard for deep learning models to explain why a particular decision they made is correct or just, that is why the decision-making importance when using such models appears to be not very clear. The quality of the performance may decline as well, for example, when there are fluctuations in the noise levels of the channel; the model may over-fit to the data employed in the optimization of the objective function. Lastly, the implementation of these techniques might require a significant modification of the current structure within the systems.

Several drawbacks are associated with the current approaches to estimating the channel for chaotic wireless communication. As an intuitive estimator, LS suffers from large noise effect when determining the channel’s impulse response, and needs many pilot symbols, which again costs bandwidth. This estimator called the Minimum Mean Square Error (MMSE) estimator is more accurate than the Size estimator but requires the noise statistics that are often difficult to estimate. Kalman filtering is very complex and demanding in terms of computational and system models, which are almost impossible to realise in chaotic dynamics. In addition, the accuracy is reduced for the non-linearities of chaotic signals where the traditional methods fail to operate efficiently. Their dynamic channel response also makes them ineffective because they are unable to adapt to changes in the channel environment. In general, these drawbacks affect the reliability and performance of conventional channel estimation methods.

III.CONCLUSION

This paper developed a new method of channel estimation by utilizing the DNN with a pre-trained SDAE. The method exploits properties of the autocorrelation function of chaotic baseband signals that are generated using a CSF. This excellent noise reduction and generalization capability of the SDAE improves channel estimation errors measured in terms of MSE, and further, the BER for chaotic wireless communication systems. Compared with a similar DNN structure without the pre-trained SDAE, the blind ACF-based analytical method, and the nonblind LS approach using a chaotic driven signal. In addition, since the training has to be done off line, the computational complexity is not a big concern; hence, this is a method useful to time-critical real-time communications applications.

IV. REFERENCE

1. J. J. Beek, O. Edfors, M. Sandell, S. K.Wilson, and P. O. Borjesson,On channel estimation in OFDM systems(Proc. IEEE VTC,New York,1995) pp. 815–819

2.O. Edfors, M. Sandell, J.-J. van de Beek, S. K. Wilson, and P. O.Brjesson, OFDM channel estimation by singular value decomposition(IEEE Trans.Commun,Wiley,1988) pp. 931–939

3 .S. Haene, A. Burg, N. Felber, and W. Fichtner, OFDM channe lestimation algorithm and ASIC implementation (Proc. IEEE Conf, HarperCollins, 2006) pp.234-241

4. M P. H. Moose, A technique for orthogonal frequency division multiplexing frequency offset correction (IEEE Trans. Commun,Bloombury,1994) pp. 2908-2914

5. Moon, JAe Kyoung and Choi, Song In, Performance of channel estimation methods for OFDM systems in multipath fading channels (IEEE conf,New York,2000) pp. 161-170.

6. Zhang Y, Wang H, Li C, et al, On the performance of deep neural network aided channel estimation for underwater acoustic OFDM communications Ocean Engineering,(Oxford: Clarendon, New York ,1892,) pp.68–73.

7. Y. Zeng, M. Pan, et al., Narcissus: A Practical Clean-Label BackdoorAttack with Limited Information(IEEE conf, wiley, 2023) pp.34-39

8.M. Qiu, K. Zhang, M. Huang, An empirical study of web interface design on small display devices, (IEEE/WIC/ACM WI'04,New York, , 2004)pp.29-35.

9.H. Qiu, M. Qiu, R. Lu, Secure V2X communication network based on intelligent PKI and edge computing, (IEEE Network 34 (2),New York, 2019)pp. 172-178.

10.M. Qiu, M. Guo, et al., Loop scheduling and bank type assignment for heterogeneous multi-bank memory, (JPDC, New York, 2009)pp. 546-558,

11. S. Hayes, C. Grebogi, and E. Ott, Communicating with chaos,(Phys.Rev. Lett,New York, 1993)pp.28-43

12. A. Dmitriev, A. Kletsov, A. Laktyushkin, A. Panas, and S. Starkov,Ultrawideband wireless communications based on dynamic chaos,(J. Commun. Technol. Electron,New York,2006) pp. 1126–1140.

13. H. P. Ren, C. Bai, Q. J. Kong, M. S. Baptista, and C. Grebogi,A chaotic spread spectrum system for underwater acoustic communication,(Physica A Stat. Mech. Appl,New York, 2017)pp. 77–92.

14. H.-P. Yin and H.-P. Ren, Direct symbol decoding using GA-SVMin chaotic baseband wireless communication system,(J. Frankl. Inst,New York,2021) pp. 6348–6367.

15. H. P. Ren, M. S. Baptista, and C. Grebogi, Wireless communication with chaos,(Phys. Rev. Lett,Ne York,2021)pp.224-233.

16. M.Jyothsna,Comparison of BER Performance Analysis of MIMO-OFDM for Different Modulation Schemes using MRRC Technique,vol-22,issue 7 pp.2062-2065.

17.M. Jyothsna, Enhanced Location Dependent key Management against Insider Threats in Wireless Sensor Networks',vol-8 issue 5