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Smart DS-CDMA Receiver Based on Feed Forward Neural Network

Drakshayini M N[a,1] and Manjunath R Kounte[a]
[a]*School of ECE, REVA University, Bangalore, India*

Abstract. Direct Sequence Code Division Multiple Access (DS-CDMA) is a schemewhere several users transmit their data simultaneously over a common wireless communication channel,by spreading each data by distinct codes. At the receiver, the individual data are detected by appropriate decoding. In this paper, a new smart receiver is proposed for detecting DS-CDMA signals based on a multi-layer Feed Forward **N**eural **N**etwork (FFNN). The proposed receiver detects the transmitted data when the received signal is distorted due to channel noise, near-far effect and Rayleigh fading. The channel state information is indirectly captured during the training of the FFNN and hence the conventional channel state estimation using pilot signal or training sequences is eliminated. Experimental results show that the performance of the proposed receiver in terms of detection accuracy is superior to similar competitive demodulators.

Keywords. Feed Forward **N**eural **N**etwork; Detection Accuracy; Walsh orthogonal signatures

1. Introduction

Direct Sequence Code Division Multiple-Access (DS-CDMA) system [1] enables multiple users to transmit synchronously using the same frequency band. Interference free Multiple-access is achieved by encoding the individual by distinct orthogonal spreading codes known as signatures (chips). DS-CDMA receivers recover one or more individual data from the received composite signal using an appropriate decoding process. The dominant problems to be solved in DS-CDMA communication system are, Multi-Access Interference (MAI), multipath fading, near-far-effect along with ubiquitous channel noise. Our objective is to present a high fidelity DS-CDMA receiver that mitigates the above-mentioned debilitating effects based on Neural Networks. The proposed method is designated as Smart Receiver based on Feed Forward Neural Network (SRFFNN).

1.1. Related ***work***

In [2], several traditional receiver designs for DS-CDMA signal detection are described in detail. In [3], the authors have designed a Sliding Bidirectional Recurrent Neural Network (SBRNN) and have shown that it is possible to train detectors which perform well without the knowledge of Channel State Information (CSI). Here, the SBRNN

[1]M. N. Drakshayini, School of ECE, REVA University, Bangalore, India. E-mail: mndrakshayini@gmail.com.

estimates the data in real time as the signal stream arrives at the receiver. This algorithm is compared with other Neural Network (NN) based detectors. It is also demonstrated that the BER performance of the proposed SBRNN detector is better than that of other NN detectors that have been proposed earlier.In [4], the authors have used NN to cancel the MAI using specialized pre-processing of the data input to the NN. The NN is trained using Levenberg-Marquardt method. Here, it is found that the bit error rate is reduced due to pre-processing.In [5], on Radial Base Function (RBF) based Multi-Layer Perceptron (MLP) is used to act as a DS-CDMA a receiver. The authors have shown that their design is superior to receivers based on Match-Filter, De-correlator Detector (DD) and MMSE. In [6], the authors have designed a two layer NN, for CDMA detection based on Fletcher-Reeves updates. They have compared the performance of their method with DD and MMSE detectors. In [7], a new DS-CDMA detector is designed based on chaotic neuron network that prevents equilibrium at local minima and achieves global minimum. In [8], fastICA algorithm is used for blind DS-CDMA detection, without any pilot or training sequences, by adopting Gold codes for signal separation. In [9], blind adaptive detection of DS-CDMA signal is implemented using the correlation matrix inversion which provides multi-accessinterference cancellation. In [10], the authors have designed a low-complexity DS-CDMA detector based on successive interference cancellation that can support a very large number of users without degradation in the quality of reception. In [11], Maximum A posteriori Probability (MAP) method is adopted for DS-CDMA detection where iteratively-decoded error-correcting codes are used for forward error correction. In [12], the authors have used Genetic Algorithm GA) and Particle Swarm Optimization(PSO) to detect DS-CDMA signals and have shown the superiority of these methods in reducing the computational complexity when the number of users is large.

2. DS-CDMA Communication Model

The basic DS-CDMA Baseband communication Model is shown in Figure 1. Here, the total number of users (code channels) is N. The input data vector $D = [d(1),.., d(i),.., d(N)]^T$ is a column vector of size Nx1 where $d(i)$ is the data input of code channel i whose signature is $S[i]$. In CDMA, the input data symbol $d(i)$ is in bipolar binary format ±1. That is, $d(i) \in \{\pm1\}$.

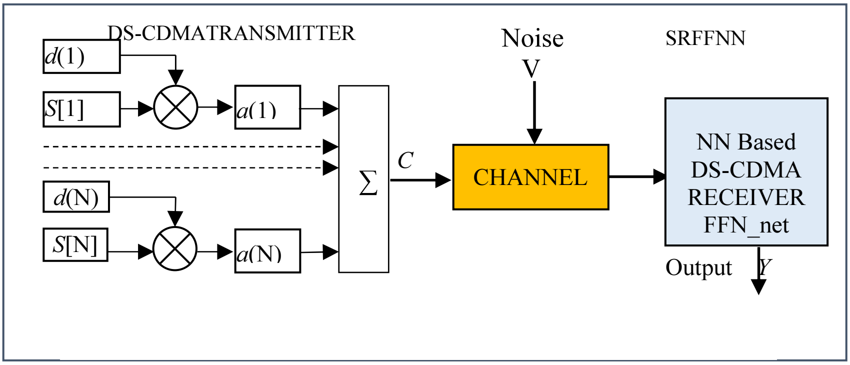

Figure 1. DS-CDMA Baseband Model

The composite base band signal C is formed from the input vector D as, $C = S[1] * d(1) * a(1) + S[2] * d(2) * a(2) + , \ldots, + S[N] * d(N) * a(N)$ and the output of the channel X is expressed as, $X = C+V$ where V is the AWGN channel noise. X is the input to the SRFFNN receiver whose output is Y which will be same as D under error-free working of the SRFFNN receiver.

2.1 Orthogonal Signatures for CDMA Encoding

In our proposed scheme SRFFNN, the Walsh orthogonal encoding signature $S[i]$'s are obtained from the columns of Hadamard matriceswhich are generated starting from $\boldsymbol{H}_2$ which is given by, $\boldsymbol{H}_2 = \begin{bmatrix} +1 & +1 \\ +1 & -1 \end{bmatrix}$. From $\boldsymbol{H}_2$, the next Hadamard Matrix $\boldsymbol{H}_4$ is obtained as, $\boldsymbol{H}_4 = \begin{bmatrix} +\boldsymbol{H}_2 & +\boldsymbol{H}_2 \\ +\boldsymbol{H}_2 & -\boldsymbol{H}_2 \end{bmatrix} = \begin{bmatrix} +1 & +1 & +1 & +1 \\ +1 & -1 & +1 & -1 \\ +1 & +1 & -1 & -1 \\ +1 & -1 & -1 & +1 \end{bmatrix}$. Matrix $\boldsymbol{H}_8$ is obtained from $\boldsymbol{H}_4$ and so on.
In general, for $n = 2, 3, 4$, *etc*,

$$\boldsymbol{H}_{2^n} = \boldsymbol{H}_N = \begin{bmatrix} +\boldsymbol{H}_{2^{(n-1)}} & +\boldsymbol{H}_{2^{(n-1)}} \\ +\boldsymbol{H}_{2^{(n-1)}} & -\boldsymbol{H}_{2^{(n-1)}} \end{bmatrix} \tag{1}$$

For convenient explanation, we take $N = 2^n$ for a suitable n (say $n = 6$, for CDMA-95). The size of $\boldsymbol{H}_N$ is NxN and it is symmetric. The DS-CDMA signature matrix $\boldsymbol{S}$ is taken as, $\boldsymbol{S} = \left(\frac{1}{\sqrt{N}}\right) * \boldsymbol{H}_N$. Then, from the property of HM, matrix $\boldsymbol{S}$ is symmetric and orthogonal as, $\boldsymbol{S}*\boldsymbol{S}^T = \boldsymbol{S}*\boldsymbol{S} = \boldsymbol{I}_{NxN}$. Matrix $\boldsymbol{S}$ can be expressed in terms of its columns as, $\boldsymbol{S} = [S[1], S[2], \ldots, S[i], \ldots, S[N]]$.

3. Smart Receiver Based on Feed Forward Neural Network

The proposed method builds a Smart Receiver based on Feed Forward Neural Network (SRFFNN) to detect the original data from the received signal in a DS-CDMA system. The FFNN used in our SRFFNN receiver is designated as FFN_net which is schematically shown in Figure 2.

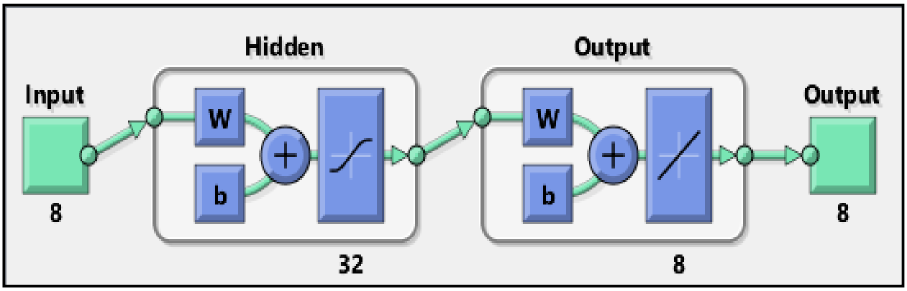

Figure 2. Schematic diagram of FFN_net (Courtesy Mathworks)

3.1 Implementation of FFN_net

FFN_net essentially works in 5 phases, namely, *creation*, *configuring*, *training*, *testing* and *application* Phase. These 5 phases are implemented using the built in functions available in Matlab [13].

FFN_net is created by feedforwardnet(…)[14] function with one hidden layer of size 32 and driven by BFGS quasi-Newton method as,

FFN_net = feedforwardnet(32,'trainbfg') (2)

The input to FFN_net is vector X and after perfect training, its desired output is D which is the transmitted data vector D.

After creation, the FFN_net is configured using the configure(…)function [14] where the sizes of the input and output layers are matched with the input and output (target) vectors X and D as,

FFN_net=configure(FFN_net,X,D) (3)

The size of vector X as well as D is Nx1. In the schematic diagram Figure 2, the value of $N = 8$.

For successful training, we need a large collection D's, which is obtained by forming a matrix represented by $\boldsymbol{DM}$ whose columns are D's. The number of columns denoted by M is chosen to be large. Thus the size of $\boldsymbol{DM}$ is NxM. Matrix $\boldsymbol{DM}$ is generated using the randi(…) function as,

$\boldsymbol{DM}$ = randi([0, 1], NxM);
$\boldsymbol{DM}$ = 2*$\boldsymbol{DM}$-1; (4)

CDMA encoding is obtained as, $\boldsymbol{X}1 = \boldsymbol{S}*\boldsymbol{DM}$ where $\boldsymbol{S}$ is the signature matrix of size NxN and the size of X1 is NxM.

The near-far effect is implemented by taking the near-far coefficients randomly in the range 0.85 to 1.15 (a spread of 15 percent) and forming the near-far matrix as,

$\boldsymbol{A}$ = 0.01*randi([85,115],N,M) (5)

Then, the resulting matrix due to the near-far effect denoted by $\boldsymbol{X}2$ is generated by element wise multiplication as,

$$\boldsymbol{X}2 = \boldsymbol{X}1.*\boldsymbol{A} \quad = (\boldsymbol{S}*\boldsymbol{DM}).*\ \boldsymbol{A} \tag{6}$$

The channel noise is taken as the AWGN with specific SNR value. The addition of noise is implemented using the awgn(…) function [15] as,

$\boldsymbol{X3}$ = awgn($\boldsymbol{X2}$,snr,'measured') (7)

This operation in Eq. (7) is actually carried out column-wise. In FNN_net training, it is found that SNR = 7 dB gives good result.

Channel fading is represented by Rayleigh Fading with L number of tapped delay coefficients randomly selected in the range 0.1 to 1.0. These are represented by H as,

H = 0.1*randi([1,10],L,1) (8)

Then, Rayleigh Fading is implemented by column-wise convolution to get the final, distorted matrix $\boldsymbol{XM}$ as,

$\boldsymbol{XM}$ = $\boldsymbol{X3}$+conv($\boldsymbol{X3}$,H,'same') (9)

The FFN_net training is carried out as,

$$\text{FFN\_net} = \text{train}(\text{FFN\_net},\boldsymbol{XM},\boldsymbol{DM}) \quad (10)$$

The training parameters like number of iterations, validation checks, are selected properly for the best performance. The size of ***XM*** as well as ***DM*** is NxM.

3.2 Test Phase

After training the FFN_net, it is tested by the function FFN_net(…) as,

$$\boldsymbol{YMT} = \text{FFN\_net}(\boldsymbol{XMT}) \quad (11)$$

In SRFFNN scheme, the CDMA data input D is a binary vector of size Nx1. Therefore, the number of distinct combinations possible for D is 2^N. The collection of these D's as columns, form the matrix ***DMT*** whose size is NxK where $K = 2^N$. The test input ***XMT*** is derived from matrix ***DMT***, similar to as ***XM*** is derived from ***DM*** as given in section 3.1, but with different parameter values for noise, near-far effect and Raleigh fading. Ideally, the output ***YMT*** of FFN_net should be equal to ***DMT***. In practice, say due to insufficient training of FFN-net or deficiency in selecting the its parameters, there can be error which is expressed as,

$$\boldsymbol{ET} = \boldsymbol{DMT} - \boldsymbol{YMT} \quad (12)$$

If ***ET*** is not zero, the FFN_net parameters are readjusted and FFN_net is trained fully and then retested until ***ET***reaches zero.In the application phase, the trained FFN_netis installed on-line to detect the real transmitted CDMA data directly without any additional processing resulting in faster detection.

Percentage Error (PE): When there is error, the Number of Errors (NE) is given by the number of non-zero elements in ***ET*** and NE is calculated as,

$$NE = \text{length}(\text{find}(\boldsymbol{ET}(:))) \quad (13)$$

The Percentage Error (PE) is obtained as,

$$PE = 100{*}NE/(\text{No.of elements in } \boldsymbol{ET}) \quad (14)$$

4. Experimental Results

Experiment 1: The FFN_net is created, configured as given by Eqs. (2) and (3). Then, it is trained by 250, 200 and 150 iterations as specified by Eq. (10).For each trial, the test matrix ***XMT*** is generated from ***DMT***, based on Eqs. (4) to (9) with *snr*in Eq. (7) decreasing from 13 dB to 6dB in steps of 1 dB. This means the channel noise level is progressively increased. The resulting PE's are shown in Table 1 in yellow background.

Table 1. Variations of PE with respect to SNR

Iterations	Method	SNR in dB							
		13 dB	12 dB	11 dB	10 dB	9 dB	8 dB	7 dB	6 dB
250	SRFFNN	0.0000	0.0000	0.0488	0.1953	0.5859	0.9766	2.2461	3.4180
	MLFFNN	0.3906	0.6592	1.2939	1.6357	2.2705	2.5391	3.6865	4.7607
200	SRFFNN	0.0488	0.0488	0.2441	0.5859	1.0254	1.6602	3.4180	4.7852
	MLFFNN	0.4883	0.6592	1.1719	2.1240	2.4170	2.7099	4.4433	5.4931
150	SRFFNN	0.0977	0.3906	0.7813	1.2695	2.1484	3.1738	4.7363	6.5918
	MLFFNN	0.8056	1.2695	1.6113	2.1484	3.0517	3.9062	5.4687	6.8115

The corresponding graph is shown in Figure 3.

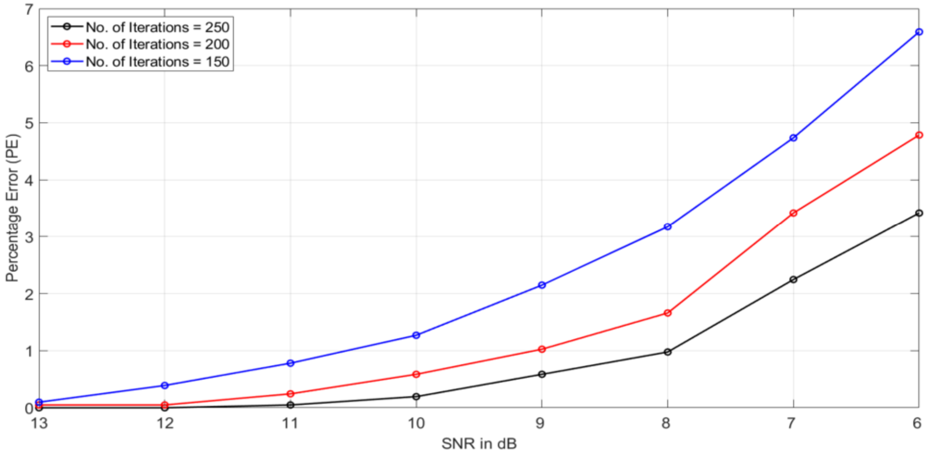

Figure 3. Variation of PE with respect to SNR for iterations 250, 200 and 100

From Figure 3, it can be seen that *PE* increases with increase in the channel noise level and PE decreases as the number of training iterations increases.

4.1Comparative performance

DS-CDMA detection by Multilayer Feed Forward Neural Network (MLFFNN)[6] method also uses NN, but the weights are updated using Fletcher-Reeves algorithm, whereas our method SRFFNN uses BFGS Quasi-Newton algorithm. Here, the PE versus SNR values are calculatedfor MLFFNNmethod, with other parameters same as in *Experiment* 1.The resulting PE values are shown in Table 1, in gray background. For the purpose of comparison, the Percentage Relative Improvement in *PE* (*PRIPE*) is defined as,

$$PRIPE \; = 100 * \frac{PE(HASSAN) - PE(SRFNN)}{PE(HASSAN)} (15)$$

Then, *PRIPE* is obtained from the values of Table 1, for iteration = 250 and SNR = 6 dB as,

$$PRIPE \; = 100 * \frac{4.7607 - 3.4180}{4.7607} = 28.2044\%$$

Similarly PRIPE's can be calculated for other values from Table 1.

The overall performance of SRFFNN is superior to other existing NN based DS-CDMA detectors in terms of Percentage Error.

5. Conclusion

A smart DS-CDMA receiver based on feed-forward Neural Network is presented. The Neural Network uses Quasi-Newton Backpropagation algorithm to adjust the weights and bias values of the Neural Network. The percentage relative improvement in percentage error of our method is found to be better by about 28% compared to its nearest similar competitive method.Percentage error can be further reduced using more than one hidden layer. Overall performance of the proposed receiver in terms of detection accuracy is superior to similar competitive demodulators.

References

[1] Mosa Ali Abu-Rgheff: Introduction to CDMA Wireless Communications, Academic Press, London. 2007. 632 p.

[2] Geert Leus, Philippe Loubaton, Dirk Slock, and Michael D. Zoltowski (Editors). Improved CDMA Detection Techniques for Future Wireless Systems. EURASIP Journal on Applied Signal Processing 2005:5, 601–603 c 2005 Hindawi Publishing Corporation.

[3] Farsad, Nariman and Andrea J. Goldsmith. Neural Network Detection of Data Sequences in Communication Systems. IEEE Transactions on Signal Processing 66 (2018): 5663-5678.

[4] B. Geevarghese, J. Thomas, G. Ninan and A. Francis. CDMA interference cancellation techniques using neural networks in Rayleigh channels.In: International Conference on Information Communication and Embedded Systems (ICICES), 2013, pp. 856-860

[5] M. S. Dastgahian, H. Khoshbin, S. Shaerbaf and A. Seyedin. DS-CDMA blind detection for frequency-selective multipath channels by neural networks. In: 5th International Symposium on Telecommunications, 2010, pp. 53-58

[6] H. A. Hassan, M. H. Essai and A. Yahya. Performance comparison of linear multiuser detectors and neural network detector for DS/CDMA systems in AWGN. In: Tenth International Conference on Computer Engineering & Systems (ICCES), 2015, pp. 307-313.

[7] Y. Xu, Z. Yang and X. Zhen. Simulated Annealing Strategy in Chaotic Neural Network with Legendre Function. In: 33rd Chinese Control and Decision Conference (CCDC), 2021, pp. 569-574.

[8] S. B. Sadkhan. A Developed DS-CDMA Detection based on ICA. In: International Conference on Communication & Information Technology (ICICT), 2021, pp. 274-278.

[9] R. Nagase, K. Oishi, T. Furukawa. An Adaptation Rule for Approximate Oblique Projector and Its Application to Blind Adaptive Detector in DS/CDMA Communication.In: International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS), 2018, pp. 284-288.

[10] J. Zhang, P. Pan, L. Yang. Dynamic DS-CDMA Aided by Successive Interference Cancellation for Massive Grant-Free Multiple-Access.In: 10th International Conference on Wireless Communications and Signal Processing (WCSP), 2018, pp. 1-7.

[11] K. Zhang, G. Tu, Y. Xie, L. Hou, C. Zhang. Joint Active User Identification and Multiuser Detection in DS-CDMA Cellular Communication Network.In: IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), 2020, pp. 2496-2501.

[12] A. Rashid, F. M. Khan and I. M. Qureshi. Genetic Algorithm based multiuser detection in DS-CDMA: A comparative analysis. In: International Conference on Machine Learning and Cybernetics, 2013, pp. 728-734.

[13] Da Silva I.N., Hernane Spatti D., Andrade Flauzino R., Liboni L.H.B., dos Reis Alves S.F. (2017) Artificial Neural Network Architectures and Training Processes. In: Artificial Neural Networks. Springer, Cham. Denmark.

[14] Howard Demuth, Mark Beale, Martin Hagan. Neural Network Toolbox 6.0.4 User's Guide: The MathWorks, Inc. 3 Apple Hill Drive Natick, MA 01760-2098. 2010. 901 p.

[15] André Quinquis, Emanuel Radoi, Cornel Ioana, Ali Mansour. Digital Signal Processing using MATLAB. John Wiley & Sons.2008, 424 p.