Radial Basis Function Neural Network Receiver Trained by Kalman Filter Including Evolutionary Techniques

Pedro Henrique Gouvêa Coelho, J. F. M. Do Amaral and A. C. S. Tome
State Univ. of Rio de Janeiro, FEN/DETEL, R. S. Francisco Xavier, 524/Sala 5001E, Maracanã, RJ, 20550-900, Brazil

Keywords: Neural Networks, Artificial Intelligence Applications, Channel Equalization, Wireless Systems.

Abstract: Artificial Neural Networks have been broadly used in several domains of engineering and typical applications involving signal processing. In this paper a channel equalizer using radial basis function neural networks is proposed, on symbol by symbol basis. The radial basis function neural network is trained by an extended Kalman filter including evolutionary techniques. The key motivation for the equalizer application is the neural network capability to establish complex decision regions that are important for estimating the transmitted symbols appropriately. The neural network training process using evolutionary techniques including an extended Kalman filter enables a fast training for the radio basis function neural network. Simulation results are included comparing the proposed method with traditional ones indicating the suitability of the application.

1 INTRODUCTION

Channel equalization is intended to mitigate the effects of the transmitted media on the transmitted symbol sequence, known as the inter-symbol interference (ISI). Adaptive equalizers are essential in these communications systems to achieve reliable data transmission. Usually two approaches are used: sequence estimation equalizers and the symbol decision equalizers. The optimal sequence estimation is yielded by MLSE (Maximum Likelihood Sequence Estimation) (Chen et. al., 1995), (Gibson and Cowan, 1989) implemented by the Viterbi algorithm. It is optimal for detecting the full transmitted sequence. High complexity in connection with the MLSE are however usually unacceptable in many typical communication systems. Most of the practical equalizers therefore employ a structure of making decision symbol by symbol. Symbol decision equalizers can still be classified into two categories according to whether they estimate a channel model explicitly. One is the direct-modelling equalizer which is not widely used once the knowledge of the channel model is needed. The other category is the indirect modelling equalizer that does not require the knowledge of the channel model. In this category, we mention among others, the linear transverse adaptive equalizers that are required in these communications systems to obtain reliable data transmission. Among the effects of wireless channels is delay dispersion, due to Multi Path Components (MPCs) having different runtimes from the transmitter (TX) to the receiver (RX). Delay dispersion causes ISI, which can largely degrade the transmission of digital signals. It is worth mention that even a delay spread that is smaller than the symbol duration can cause a significant Bit Error Rate (BER) degradation. If the delay spread becomes comparable with or larger than the symbol duration, as occurs often in third and fourth generation cellular systems, then the BER turns unacceptably large if no compensation are performed. Also when a signal is transmitted through wireless medium then due to multipath effect there is fluctuation in signal amplitude, phase, and time delay. This effect is often known as fading (Proakis, 2001). The use of coding and diversity can decrease, but not fully eliminate, errors due to ISI. However, delay dispersion can also be a positive effect. Since fading of the distinct MPCs is statistically independent, resolvable MPCs can be modeled as diversity paths. So, delay dispersion allows the possibility of delay diversity, if the RX can extract, and exploit, the resolvable MPCs. Equalizers can be interpreted as devices that work both ways - they decrease or eliminate ISI, and simultaneously exploit the delay diversity inherent

Coelho, P., M. Do Amaral, J. and Tome, A.
Radial Basis Function Neural Network Receiver Trained by Kalman Filter Including Evolutionary Techniques.
DOI: 10.5220/0009565806260631
In *Proceedings of the 22nd International Conference on Enterprise Information Systems (ICEIS 2020) - Volume 1*, pages 626-631
ISBN: 978-989-758-423-7

in the channel. The principle of an equalizer can be analyzed either in the time or frequency domain. In the present work the time-domain method is taken which is feasible in most of the applications. Usually, the channel response may not be known at startup. Besides, the channel may be time-varying, so an adaptive structure of the equalizer is essential. One can identify distinct modes of adaptation:

• A training signal aided adaptation;

• Decision directed adaptation - An error signal defined by comparing input and output of the decision device;

• Blind adaptation: Signal properties aided adaptation instead of making use an error signal;

A training signal is considered in this article for the equalizer adaptation. It should be stressed that, digital communication systems typically operate on time varying dispersive channels which usually employ a signaling format in such way that user data are set up in blocks preceded by a known training sequence. That training sequence at the beginning of each block is used to estimate channel or train an adaptive equalizer. Depending on the rate at which the channel changes with time, there may not be a need to further track the channel variations during the user data sequence. The present article proposes a channel equalizer for wireless channels using Radial Basis Function (RBF) neural networks including evolutionary techniques on a symbol by symbol decision basis. Their use was spread by (Moody and Darken, 1989), and has proven to be useful neural network architecture. The major difference between RBF networks and back propagation networks is the behavior of the single hidden layer. Rather than using the sigmoidal or S-shaped activation function as in back propagation, the hidden units in RBF networks use a Gaussian or some other basis kernel function. Each hidden unit acts as a locally tuned processor that computes a score for the match between the input vector and its connection weights or centers. In effect, the basis units are highly specialized pattern detectors. The weights connecting the basis units to the outputs are used to take linear combinations of the hidden units to product the final classification or output. The RBF equalizer classifies the received signal according to the class of the center closest to the received vector (Assaf et al, 2005), (Burse et al, 2010). The output of the RBF equalizer offers an attractive alternative to the Multi-Layer Perceptron (MLP) type of Neural Network for channel equalization problems because the structure of the RBF network has a close relationship to Bayesian methods for channel equalization and interference exclusion. RBF networks comprise three layers: the input layer, the hidden layer with the RBF nonlinearity, and a linear output layer, as shown in Fig. 1(Burse et al, 2010). This paper is divided into four sections. Section 2 does a brief discussion of RBF artificial neural networks. Section 3 presents the RBF neural net equalizer and case studies and section 4 ends the paper with conclusions.

2 RBF NEURAL NETS

RBF neural networks are a very popular architecture only surpassed by feedforward neural networks. Denoting the input (vector) as x and the output as y(x) (scalar), the architecture of a RBF neural network is given by

$$\mathrm{y(x)} = \sum_{i=1}^{M} w_i \exp\left(-\frac{(\| x - c_i \|)^2}{2\sigma^2} \right) \tag{1}$$

using Gaussian function as basis functions. Observe that, $\mathbf{c}_i$ are called centers and σ is called the width. There are M basis functions centered at $\mathbf{c}_i$, and w_i are named weights.

RBF neural networks are very popular for function approximation, curve fitting, time series prediction, control and classification problems. The radial basis function network differs from other neural networks, showing many distinctive features. Due to their universal approximation, more concise topology and quicker learning speed, RBF networks have attracted considerable attention and they have been widely used in many science and engineering fields (Oyang et al., 2005), (Fu et al., 2005), (Devaraj et al., 2002), (Du et al., 2008), (Han et al., 2004). The determination of the number of neurons in the hidden layer in RBF networks is somewhat important because it affects the network complexity and the generalizing capability of the network. In case the number of the neurons in the hidden layer is insufficient, the RBF network cannot learn the data adequately. On the other hand, if the number of neurons is too high, poor generalization or an overlearning situation may take place (Liu et al., 2004). The position of the centers in the hidden layer also influences the network performance significantly (Simon, 2002), so determination of the optimal locations of centers is an important job. Each neuron has an activation function in the hidden layer. The Gaussian function, which has a spread parameter that controls the behavior of the function, is the most preferred activation function. The training method of RBF networks also includes the optimization of spread parameters of each neuron. Later on, the weights between the hidden layer and the output layer must be selected suitably. Finally, the bias values which are added with each output are determined in the RBF network training procedure. In the literature, several algorithms were proposed for training RBF networks, such as the gradient descent (GD) algorithm (Karayiannis, 1999) and Extended Kalman filtering (EKF) (Simon, 2002). Several global optimization methods have been used for training RBF networks for different science and engineering problems such as genetic algorithms (GA) (Barreto et al., 2002), the particle swarm optimization (PSO) algorithm (Liu et al., 2004), the artificial immune system (AIS) algorithm (De Castro et al., 2001) and the differential evolution (DE) algorithm (Yu et al., 2006). The Artificial Bee Colony (ABC) algorithm is a population based evolutional optimization algorithm that can be used to various types of problems. The ABC algorithm has been used for training feed forward multi-layer perceptron neural networks by using test problems such as XOR, 3-bit parity and 4-bit encoder/decoder problems (Karaboga et al., 2007). Due to the need of fast convergence, EKF training was chosen for the RBF equalizer reported in this paper including evolutionary techniques briefly depicted in the next section. Details on the training process can be found in (Simon, 2002).

3 RBF EQUALIZATION DEVICE

Radial Basis Function Neural Networks have been used for channel equalization purposes (Lee et al., 1999), (Gan et al., 1999), (Kumar et al. 2000), (Xie and Leung, 2005). Typically, such networks have three layers: the input layer, the hidden layer with the RBF nonlinearity, and a linear output layer, as shown in Fig. 1 (Burse et al., 2010). Simulations carried out on time-varying channels using a Rayleigh fading channel model to compare the performance of RBF with an adaptive maximum likelihood sequence estimator (MLSE) show that the RBF equalizer produces superior performance with less computational complexity (Mulgrew, 1996). Several techniques have been developed in literature to solve the problem of blind equalization using RBF (Tan et al., 2001), (Uncini et al., 2003) and others. RBF equalizers require less computing demands than other equalizers (Burse et al., 2010).

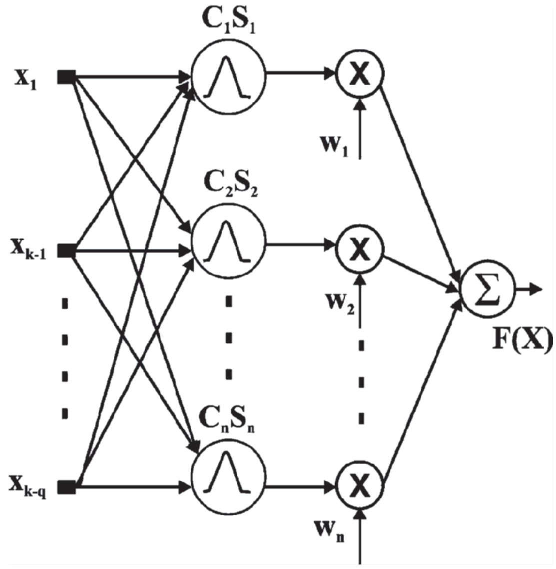

Figure 1: RBF neural network (from Burse et al., 2010).

A comprehensive review on channel equalization can be found in (Qhreshi, 1985). A recent review on Neural Equalizers can be found in (Burse et al., 2010). The equalization scheme can be seen in Fig. 2 (taken from (Molisch, 2011)). The adaptive equalizer in the figure is the RBF Neural equalizer trained by EKF according to (Simon, 2002) including evolutionary techniques. The considered channel uses the Rayleigh model (Molisch, 2011) using QPSK modulation.

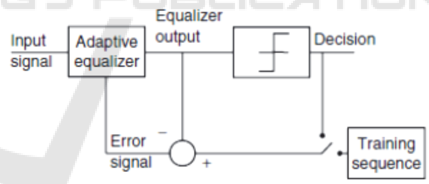

Figure 2: Equalization procedure (from Molisch, 2011).

The QPSK ideal constellation symbols are shown in figure 3. In other words when the communications channel is ideal, there is no distortion or noise so that the symbols are always received with no error. For a real channel the received symbols will show some dispersion as shown in figure 4.

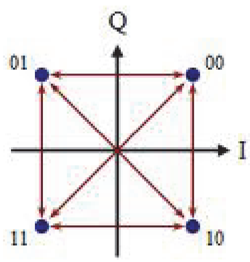

Figure 3: QPSK ideal constellation.

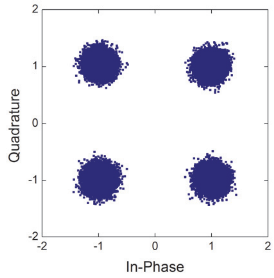

Figure 4: QPSK real scenario constellation.

The evolutionary techniques used in connection to extended Kalman filtering training of the RBF equalizer take into account the differential evolutionary (DE) approach (Brownlee, 2011). (Souza et al., 2007) used it in a Kalman filter trained RBF arrangement for forecasting the soybean price. The DE technique basically involved the estimation of the main diagonal of matrices P, Q and R that are respectfully the filter error covariance matrix, the system noise covariance matrix and the observation noise covariance matrix. The fitness function for the DE technique is the multiple correlation coefficient which measures the fitness of the model with measured data. A value close to 1 indicates the model is adequate (Brownee, 2011). Several simulations were carried out for realistic channel characteristics. Two case studies were considered. For the first case study, a flat fading channel was considered. Flat fading channels have amplitude varying channel characteristics and are narrowband (Molisch, 2011). A transmission of an image was considered in both case studies. The transmitted image is depicted in figure 5.

Figure 5: Original transmitted image in case studies.

The simulations also made possible to plot results for comparing the performance in terms of Bit Error Rate (BER) against Signal to Noise Ratio (SNR) and Symbol Error Rate (SER) against SNR. The received image for the RBF equalizer and the Decision Feedback Equalizer (DFB) which is a quite popular traditional equalizer is shown in figures 6 and 7. The simulated RBF equalizer produced an average correlation coefficient of 0.993 with standard deviation of 0.085 and used 7 Gaussian functions in the hidden layer. The computational complexity of the DFB was chosen to be comparable to the RBF equalizer.

Figure 6: RBF received image for flat fading.

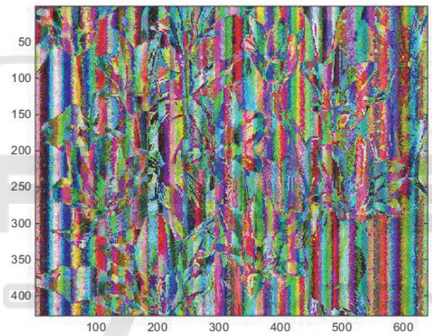

Figure 7: DFB received image for flat fading.

In a qualitative way, one can see that the RBF equalizes better. For a quantitative description figure 8 shows the BER x SNR and SER x SNR for the two equalizers. The theoretical curve is also shown for comparative purposes. One can see that the RBF equalizer performs better as the images of the received figures indicated. It can be also seen that for low SNRs the performance of the RBF equalizer is very close the theoretical performance. As SNR values increase the equalizer begins to get away from the theoretical model. Figure 9 shows a constellation diagram for the equalizers in case study 1, and it can be seen a cluster formation around the original symbols for both equalizers, indicating that errors might occur in the receiver output. The constellation diagram is a qualitative way of comparing the performance of received symbols and complements the information given by the curves BER x SNR. Usually are made available in displays of measurements instruments for maintenance purposes.

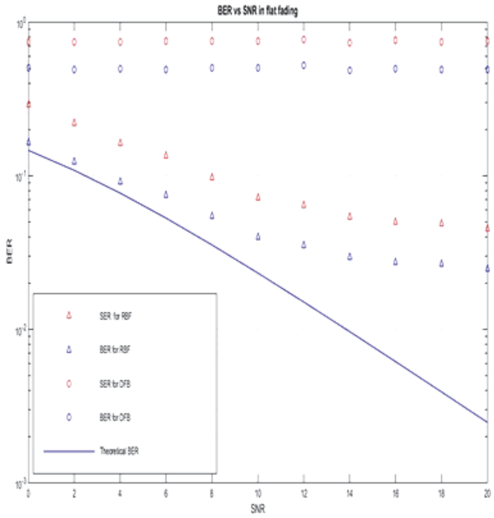

Figure 8: BER x SNR for case study 1.

Figure 9 shows a constellation diagram for the equalizers in case study 1, and it can be seen a cluster formation around the original symbols for both equalizers, indicating that errors might occur in the receiver output.

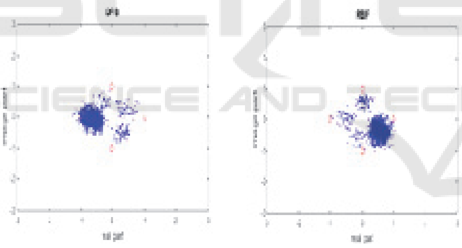

Figure 9: Constellation diagram for case study 1.

In case study 2, a frequency selective fading was considered which is a more severe type of fading (Moslisch, 2010). Figures 10 and 11 show the received images corresponding to RFB and DFB

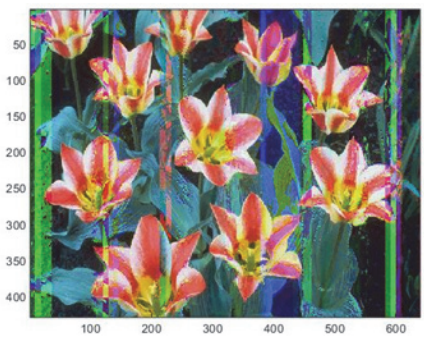

Figure 10: RBF received image for case study 2.

equalizers. One can see a more intensive degradation in the image for both equalizers, although the DFB is still worse. The performance curves are depicted in figure 12 which shows clearly the degradation in performance for both equalizers as far as frequency selective fading is concerned.

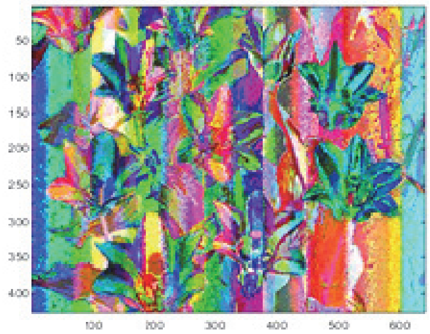

Figure 11: DFB received image for case study 2.

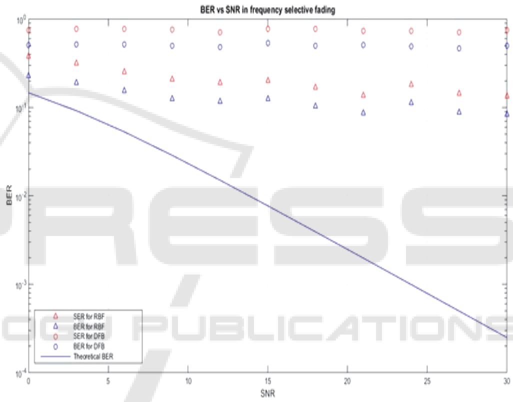

Figure 12: BER x SNR for case study 2.

4 CONCLUSIONS

This paper proposed a radial basis function (RBF) equalizer trained by an extended Kalman filter (EKF) using DE techniques. The advantages of using a Kalman filter for training the RBF neural equalizer are that it provides the same performance as gradient descent training, but with much less of the computational effort. Moreover if the decoupled Kalman filter is used in connection with DE techniques, the same performance is guaranteed with further decrease on the computational effort for large computational demand problems. The equalizer was tested and two case studies were carried out where its performance was compared with the popular Decision feedback equalizer and the results indicated the proposed equalizer performed better. For future work the authors intend to consider hybrid solutions involving the RBF and other equalizer architectures as far as the tracking of time-variations is concerned. In this respect the use of deep learning techniques might be an attractive way of achieving such a purpose.

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