Int. J. Electron. Commun. (AEÜ) 73 (2017) 150–156

Contents lists available at ScienceDirect

International Journal of Electronics and Communications (AEÜ)

journal homepage: www.elsevier.com/locate/aeue

Regular paper

Neural networks applications for CDMA systems in non-Gaussian multi-path channels ☆

Hasan Abu Hilal

Electronics Engineering Department, ADMC, Abu Dhabi, United Arab Emirates
Higher Colleges of Technology (HCT), Abu Dhabi, United Arab Emirates

ARTICLE INFO

Article history:
Received 19 April 2016
Accepted 10 January 2017

Keywords:
CDMA
Impulsive noise
Neural networks
Multiuser detection

ABSTRACT

Non-Gaussian noise is one of the most common noise models observed in wireless channels. This type of noise has severe impact on wireless systems with multiuser detection devices. In this paper, the issue of multiuser detection in non-Gaussian noise multipath channel is addressed. We also pay a close attention to the neural network applications, and propose a new robust neural network detector for multipath impulsive channels. The maximal ratio combining (MRC) technique is adopted to combine the multipath signals. Moreover, we discuss the performance of the proposed multiuser neural network decorrelating detector (NNDD), under class A Middleton model. Furthermore, the performance of the system under power imbalance scenario is shown. We show that the proposed NNDD has magnificent effect on the system performance. The system performance is measured through the bit error rate (BER). It is shown that the proposed robust receiver reduces the impact of the impulsive noise by processing the received signal and clipping the extreme amplitudes.

1. Introduction

In many signal processing applications, the noise is modelled as a Gaussian model. To justify this assumption, the central limit theorem is usually used. In many physical channels, such as urban, indoor radio channels and underwater acoustic channels, the ambient noise is known to be non-Gaussian, due to impulsive man-made electromagnetic interference. This led to further research on impulsive channels, and the demodulation of these signals [1,2].

Joint detection techniques have been used to reduce the effect of multiple access interference (MAI) and increase system performance. The interference by other users in a code division multiple access (CDMA) system has been recognized as the capacity-limiting factor. Multiuser detection in CDMA systems [3] has been well researched since the pioneering work by Verdu [4], that demonstrated a potential increase in capacity that multiuser detectors provide over conventional detectors.

Conventional CDMA detection focuses on single user signal detection, and considers all other users' signal as noise. Whereas joint detection considers the remaining users' signal as available information. Therefore, joint detection increased the capacity of CDMA, especially in the near/far scenarios. CDMA multiuser detection is an effective way to enhance the uplink system.

In [5] Optimum multiuser detectors have exponential computational complexity. Low complexity multiuser detectors have been proposed [6,7], such as the Decorrelating Detector, MMSE parallel and successive interference cancellation detectors. Some sub-optimal detectors such as successive interference cancellation (SIC) multiuser scheme performs well in CDMA and multi input multi output (MIMO) CDMA systems. However, this detector requires precise estimation of the channel parameters when successively cancelling the information of every user from the total received signal during the detection process [8,9]. Multiuser approaches have largely alleviated the problem when the noise process is additive Gaussian. With the availability of multiuser detectors, inaccurate or inappropriate noise modelling assumptions deteriorate the performance of these detectors [10–14].

Feedforward neural networks, also known as multilayer perceptrons, with one hidden layer have been demonstrated of approximating any function with any degree of accuracy. Neural networks are found in a variety of disciplines including computer science, engineering, and medicine [15–20]. Some have used neural networks for CDMA detection. Such as blind adaptive multiuser detection technique [21], whose performance tends to the MMSE detector without requiring any training sequence and was proposed in [22,23].

☆ Higher Colleges of Technology.
E-mail address: hasanabuhilal@hotmail.com
URL: http://www.hct.ac.ae

http://dx.doi.org/10.1016/j.aeue.2017.01.006
1434-8411/

Multipath fading significantly degrades the bit error rate (BER) performance. Therefore, fading compensation is generally required to reduce the multi-path effects. In [24], a novel adaptive path selective fuzzy decorrelating detector (APSFDD) under impulsive noise for multi-path fading CDMA systems was proposed. APSFDD combines adaptive path selective decorrelating detector (APSDD) [25] with a preprocessing fuzzy median filter, based on the fuzzy rank ordering of samples to remove the influence of the impulsive noise. This allowed APSDD to perform effectively in non-Gaussian channels.

Neural networks application is widely used in CDMA detection [26,27]. In this paper, the issue of multiuser detection in multipath fading CDMA channels under impulsive noise is researched. Specifically, feedforward neural network multipath decorrelating detector, with maximal ratio combining (MRC), and binary phase shift keying (BPSK) signals is employed to reduce the interference, and the non-Gaussian background noise. Clipping is one of the commonly used techniques to mitigate the impulsive effects, using a chip-based soft-limiting clipper before the decorrelation operation, the effects of extreme amplitudes are then reduced [28,29].

In [30,31] a study on soft-limiting clipper for single-user detection was conducted, the optimal threshold value was adjusted to minimize the output BER. This requires independent search for each value of the signal to noise ratio (SNR). In [32], a simplified threshold value which is a function of the chip amplitude and the processing gain was presented. This threshold can be used for each value of the SNR and is effective in reducing the extreme amplitudes without a significant increase in complexity. In this work, neural network decorrelating detector is proposed, where no threshold value complication is required. Adjusting the threshold to minimize the BER is usually done by trials, which is time consuming. The simplified version of thresholding is still complicated, however, with the available fast electronic chips and systems, neural network decorrelating detector would be advantageous. It does not need threshold examinations. It needs a training sequence to train the network, then, the received signal will be filtered by the weights of the trained network. Finally, a clean filtered signal is obtained in contrast to the heavy search on the threshold values. In [33,34] there are more information on neural network, decorrelating detector and Parallel Interference Cancellation (PIC) topic.

The organization of this paper is as follows. Following the introduction in Section 1. The CDMA signal components are stated in Section 2, which describes the detection technique in CDMA, and the impulsive noise characteristics. Section 3, shows The structure of the Robust neural networks multipath detector. Numerical evaluations and simulation results are presented in Section 4. Conclusions are stated out in Section 5.

2. The system model

A CDMA system with K users is considered, where the signature waveforms of all the users are assumed to be known at the receiver. The received multipath signal at the receiving antenna is:

$$r(t) = \sum_{k=1}^{K} A_k b_k \sum_{l=1}^{N_p} c_{k,l} s_k(t-(l-1)T_c) + n(t), \tag{1}$$

where the subscript k stands for the user index, A_k is the received amplitude and $b_k \in \pm 1$ denotes the transmitted bit, $s_k(t)$ is the real-valued unit-energy spreading sequence of length L with support $[0, T]$, N_p is the number of resolvable paths of the channel, $c_{k,l}$ is the channel coefficient of the l^{th} path of the channel. It is assumed that the delay of each path of the channel is spaced at T_c time intervals where T_c is the chip period of the spreading sequence. The channel is assumed to vary slowly such that it can be assumed to be constant over a bit transmission. The ambient impulsive noise $n(t)$ is complex with real and imaginary parts which are independent and each has a power spectral density of $No/2$. The impulsive noise adopted in this paper is the commonly used two-term Gaussian mixture model. The probability density function (pdf) of this noise model has the form:

$$f = (1-\epsilon)G(0, v^2) + \epsilon G(0, \kappa v^2), \tag{2}$$

with $v > 0, 0 \leqslant \epsilon \leq 1$, and $\kappa \geqslant 1$. Here, the $G(0, v^2)$ term represents the nominal background noise, and the $G(0, \kappa v^2)$ term represents impulsive components, with ϵ representing the probability that impulses occur. It is common to study the effects of variation in the shape of a distribution on the performance of the system by varying the parameters ϵ, and κ and with fixed total noise variance

$$\sigma^2 = (1-\epsilon)v^2 + \epsilon\kappa v^2, \tag{3}$$

This noise model serves as an approximation to the more fundamental Middleton Class A noise model, and has been used extensively to model physical noise arising in radio and acoustic channels. Fig. 1 represents a sample of the impulsive noise, where the peaks are easily seen.

3. Neural networks detector

In this section, the neural network model is first illustrated, hence the concept of the neural network lies at the heart of this research. The neuron model used is the tansig function. The elementary neuron model has a vector of inputs, each input is weighted with an appropriate weight. The sum of the weighted inputs and the bias forms the input to the transfer function. The neurons can use any differentiable function transfer function. In this work, the tan sigmoid function is considered. First we depict the hidden layer and the output layer of the neural network model. A tansig and symmetric saturating line function is used at the output of the hidden layer and the output layer respectively. As shown in Fig. 2. The input vector **P** is first multiplied by the weights **W1** of the hidden layer. The size of the input vector is depending on the number of users, number of frames and the spread sequence length. After that the output signal is processed by a tansig function. In the second phase of the process, the output of the hidden layer **a** is multiplied by the output layer weights **W2** and a final output is found through the sline function. These weights are found by a training sequence in the received data vector. We use two layer perceptron network as shown in Fig. 3, where the output

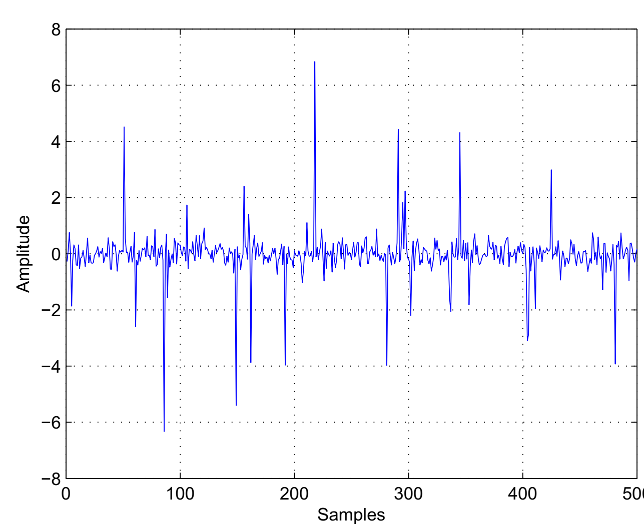

Fig. 1. Impulsive noise sample, $\epsilon = 0.1, \kappa = 100$.