

Hopfield Neural Network for UWB Multiuser Detection

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Abstract: -The Hopfield neural network (HNN) is introduced in the paper and is proposed as an effective multiuser detection in direct sequence-ultra-wideband (DS-UWB) systems. It can approximate to maximum likelihood (ML) detector by mathematical analysis. According to the HNN-based technique, the computer simulation results show that they have good performances and much lower computational complexity in a multiuser environment.

Keywords: - Maximum likelihood, Neural network, Hopfield.

1 Introduction

Ultra-wideband (UWB) transmission has recently attracted a great amount of attention in both academia and industry for applications in wireless communications [1-6]. The UWB systems can perform very high transmission data rate, and they are mainly applied to the indoor transmission. According to [3], the transmission data rate can get up to 100 Mbps at the transmission distance of 10 meters, and it arises to 200 Mbps when the transmission distance is reduced to 4 meters. In the aspect of video application, the UWB wireless transmission may replace the complex wired cable line. At present, the UWB systems still consume electricity. Its major application has contained transmission between DVD player and HDTV. In the future, the UWB systems that consume low electricity are applied to many portable devices. In the wireless communication systems, we encounter some problems such as channel estimation, symbol synchronization and multiuser detection. In the different multipath indoor environments, the UWB systems also endure multipath interference (MPI). With the increase of user number, the multiuser UWB systems will cause serious the multiuser interference (MUI). Hence, it is important to solve MUI and MPI effects. One solution to this problem is to use the multiuser detection. We can use the optimal multiuser detector based on the maximum likelihood (ML) rule proposed by Verdu [7] for Code-Division Multiple-Access (CDMA) systems. In the UWB systems, the optimal multiuser detection based on ML rule was proposed by [8]. Its performance is optimal, but its computational complexity grows exponentially with the number of users. Several suboptimum multiuser detection schemes have been proposed in CDMA systems [9-11] to reduce the high complexity.

Some authors proposed to use neural network to reduce the computational complexity, such as multilayer perception (MLP) [12], RBF network [13] and Hopfield network [14-15].

In the paper, we propose a multiuser detector, which realizes near ML detector by using Hopfield neural network (HNN) technology in DS-UWB systems. A Hopfield net is a form of recurrent artificial neural network invented by John Hopfield [16]. Hopfield nets serve as content-addressable memory systems with binary threshold units. For the multiuser detection, we apply a neural algorithm proposed by [17] to approximate to ML function. The remainder of the paper is organized as follows. In Section 2, the model of DS-UWB systems and common detectors are introduced. In Section 3, the HNN detector is introduced and studied in DS-UWB systems. The simulation results are shown in Section 4. Finally, conclusions are given in Section 5.

2 System Model

2.1 Transmitter Model

We consider a K -users DS-UWB system over the UWB indoor multipath fading channels, where each user employs unique DS spreading code. The transmitted base band signal $q_k(t)$ for the k th user is obtained by spreading a set of binary phase-shift keying (BPSK) data symbol $\{b_k[i]\}$ onto a spreading waveform $s_k(t)$, which is written as

$$q_k(t) = \sqrt{E_k} \sum_{i=1}^P b_k[i] s_k(t - iT_b), \quad (1)$$

where E_k is the symbol energy of the k th user, P is the packet size, $b_k[i] \in \{\pm 1\}$ is the i th data symbol of the k th user, and T_b is the symbol interval duration. The spreading waveform $s_k(t)$ is also written as

$$s_k(t) = \frac{1}{\sqrt{G}} \sum_{n=0}^{N_c-1} c_{k,n} w(t - nT_c) \quad (2)$$

where $G = \sum_{n=1}^{N_c} c_{k,n}^2$, $k=1,2,\dots,K$, $c_{k,n} \in \{\pm 1\}$ is the n th chip of the k th user, N_c is the chip numbers, T_c is the chip interval duration, and $w(t)$ is the chip waveform of duration $T_c = T_b / N_c$.

2.2 Channel Model

The UWB indoor channel model is based on the Saleh-Valenzuela (S-V) approach [18] where the impulse response is composed of the exponential decay clusters to model the dense multipath components. For the UWB indoor transmission environment, the channel impulse response of UWB indoor channel model is formulated as follows:

$$\begin{aligned} h_k(t) &= \sum_{l=1}^{L_k} \alpha_{k,l} \delta(t - \tau_{k,l}) \\ &= \sum_{l=1}^{L_k} \alpha_{k,l} \delta(t - (l-1)T_c), \end{aligned} \quad (3)$$

where L_k denotes the total number of propagation paths of the k th user, $\alpha_{k,l}$ is the channel coefficient of the l th path of the k th user and $\tau_{k,l}$ is the multipath delay of the l th path of the k th user. In this paper, we suppose that the multipath delay $\tau_{k,l}$ is an integral multiple of T_c .

2.3 Receiver Model

When passing the signal through the indoor environment, the obstacles in the transmitted path will cause the multipath transmission. Therefore, the total received signal can be formulated as follows:

$$r(t) = \sum_{k=1}^K \sqrt{E_k} \sum_{i=1}^P b_k[i] v_k(t - iT_b) + n(t), \quad (4)$$

where $v_k(t) = s_k(t) \otimes h_k(t)$ and \otimes is linear convolution, is defined as template signal of the k th user, which is a convolution between the k th user's

spreading code and channel coefficient, $n(t)$ is zero-mean additive white Gaussian noise. Hence, the discrete-time received signal after sampling (iT_b) is written as follows:

$$y_k[i] = \sum_{m=1}^K \sqrt{E_m} \sum_{j=1}^P b_m[j] R_{m,k}[j, i] + \tilde{n}_k[i] \quad (5)$$

where

$$R_{m,k}[j, i] = v_m[i - j] \otimes v_k^*[-i],$$

$$\tilde{n}_k[i] = n[i] \otimes v_k^*[-i].$$

Besides, output vector of the bank of K matched filter outputs [7] can be written as follows:

$$\mathbf{y} = \mathbf{R}\mathbf{A}\mathbf{b} + \tilde{\mathbf{n}}, \quad (6)$$

where $\mathbf{y} = [y_1[1], y_2[1], \dots, y_{K-1}[P], y_K[P]]^T$ is the received signal vector, \mathbf{R} is the crosscorrelation matrix which is $KP \times KP$ dimensional matrix, $\mathbf{A} = \text{diag}\{\sqrt{E_1}, \dots, \sqrt{E_K}, \sqrt{E_1}, \dots, \sqrt{E_K}, \sqrt{E_1}, \dots, \sqrt{E_K}\}$ is the transmitted amplitude matrix, $\mathbf{b} = [b_1[1], b_2[1], \dots, b_{K-1}[P], b_K[P]]^T$ is transmitted bit vector and $\tilde{\mathbf{n}} = [\tilde{n}_1[1], \tilde{n}_2[1], \dots, \tilde{n}_{K-1}[P], \tilde{n}_K[P]]^T$ is a Gaussian random variable with zero-mean and covariance matrix $\sigma^2 \mathbf{R}$. Their expressions are formulated as follows:

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}[1,1] & \mathbf{R}[1,2] & \cdots & \mathbf{R}[1,P] \\ \mathbf{R}[2,1] & \mathbf{R}[2,2] & \cdots & \mathbf{R}[2,P] \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{R}[P,1] & \mathbf{R}[P,2] & \cdots & \mathbf{R}[P,P] \end{bmatrix}$$

$$\mathbf{R}[i, j] = \begin{bmatrix} R_{1,1}[i, j] & R_{1,2}[i, j] & \cdots & R_{1,K}[i, j] \\ R_{2,1}[i, j] & R_{2,2}[i, j] & \cdots & R_{2,K}[i, j] \\ \vdots & \vdots & \ddots & \vdots \\ R_{K,1}[i, j] & R_{K,2}[i, j] & \cdots & R_{K,K}[i, j] \end{bmatrix}$$

where $\mathbf{R}[i, j]$ is a $K \times K$ dimensional matrix.

2.4 Multiuser Detectors

2.4.1 Conventional Detector

The signal that received by a Conventional Detector (CD) can be detected:

$$\hat{b}_k^{CD}[i] = \text{sgn}\{y_k[i]\}, \quad (7)$$

2.4.2 Decorrelating Detector

The decorrelating detector (DD) applies the matrix \mathbf{R}^{-1} to the output of the matched filter:

$$\hat{\mathbf{b}}^{DD} = \text{sgn}\{\mathbf{R}^{-1}\mathbf{y}\}, \quad (8)$$

2.4.3 Minimum Mean Square Error Detector

The MMSE detector which considers the background noise has also affected the output of the channel matched filters.

$$\hat{\mathbf{b}}^{MMSE} = \text{sgn}\left\{\left(\mathbf{R} + \sigma^2 \mathbf{A}^{-2}\right)^{-1} \mathbf{y}\right\}, \quad (9)$$

2.4.4 Maximum Likelihood Detector

According to [19], the optimal multiuser detector can be achieved by maximum a posteriori (MAP) estimation. Because the probability of $b_k[i]=1$ is equal to the probability of $b_k[i]=-1$, the ML estimation can be generalized by the MAP estimation. The formula of ML detector is written as follows:

$$\hat{\mathbf{b}}^{ML} = \arg \max_{\mathbf{b} \in \{-1, +1\}^{KP}} [2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b}], \quad (10)$$

3 Hopfield Neural Network Multiuser Detector

A Hopfield network was proposed by Hopfield in 1982 [16], and it was a network of associative memories. The Hopfield network that is a kind of neural network is single layer networks with output feedback consisting of simple neurons that can collectively provide good solutions to difficult optimization problems. The typical HNN algorithm with N neurons is formulated as follows:

$$\begin{aligned} X_l(m) &= \text{sign}\{U_l\} \\ &= \text{sign}\left\{\sum_{j=1}^N W_{l,j} X_j(m-1) - V_l\right\}, \end{aligned} \quad (11)$$

where $W_{l,j}$ is the connection weight between the output of the j th neuron and the input of the l th neuron, $X_l(m)$ that is the output of l th neuron at the m th iteration is

either +1 or -1, V_l that is the decision threshold of the l th neuron has the range $-1 < V_l < 1$ and U_l is network weighting value of the l th neuron. The $\text{sign}\{\}$ is signum activation. The connection weights of HNN have the following restrictions:

$W_{l,l} = 0, \forall l$ (no neuron has connection with itself)

$W_{l,j} = W_{j,l}, \forall j, l$ (connections are symmetric)

The above restrictions are used and then the equations of motion for the activation of the neurons of the HNN always lead to convergence to a stable state. If non-symmetric weights are be used, the network may exhibit chaotic behavior. In order to understand the process of HNN, we must analyze it by the viewpoint of energy. This viewpoint is from Lyapunov function [20]. According to Lyapunov function, the state of motion is equal to the equilibrium of system if the energy achieves to minimum. In the discrete HNN with N neurons, an energy function which is considered to be a Lyapunov function is defined to express the energy of network, and it is formulated as follows:

$$E(m) = -\frac{1}{2} \sum_{l=1}^N \sum_{j=1}^N W_{l,j} X_l(m) X_j(m) + \sum_{l=1}^N V_l X_l(m), \quad (12)$$

where $X_l(m)$ is the state value of the l th neuron, $X_j(m)$ is the state value of the j th neuron, $W_{l,j}$ is the connection weight between the l th neuron and the j th neuron, and V_l is the decision threshold of the l th neuron. Besides, the energy function of HNN can be rewritten by vector-matrix,

$$E(m) = -\frac{1}{2} \mathbf{X}^T(m) \mathbf{W} \mathbf{X}(m) + \mathbf{V}^T \mathbf{X}(m). \quad (13)$$

where

$$\mathbf{X}(m) = [X_1(m), X_2(m), \dots, X_N(m)]^T$$

$$\mathbf{V} = [V_1, V_2, \dots, V_N]^T \text{ and}$$

$$\mathbf{W} = \begin{bmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,N} \\ W_{2,1} & W_{2,2} & \cdots & W_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ W_{N,1} & W_{N,2} & \cdots & W_{N,N} \end{bmatrix},$$

with $W_{l,l} = 0$, for $l = 1, 2, \dots, N$.

The optimum multiuser detection based on the ML decision was proposed by Verdu [7]. Its performance is optimal, but its time complexity grows

exponentially with the number of users. In order to reduce computational complexity, we employ the HNN detector that can approximate to ML detector in DS-UWB systems.

Recall (10), it can be rewritten as follows:

$$\begin{aligned}
 \hat{\mathbf{b}}^{\text{ML}} &= \arg \max_{\mathbf{b} \in [-1, +1]^{KP}} [2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b}] \\
 &= \arg \max_{\mathbf{b} \in [-1, +1]^{KP}} [2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{H} \mathbf{b}] \\
 &= \arg \min_{\mathbf{b} \in [-1, +1]^{KP}} [-2\mathbf{b}^T \mathbf{A} \mathbf{y} + \mathbf{b}^T \mathbf{H} \mathbf{b}] \\
 &= \arg \min_{\mathbf{b} \in [-1, +1]^{KP}} \left[-\mathbf{b}^T \mathbf{A} \mathbf{y} + \frac{1}{2} \mathbf{b}^T \mathbf{H} \mathbf{b} \right] \\
 &= \arg \min_{\mathbf{b} \in [-1, +1]^{KP}} \left[-\mathbf{b}^T \mathbf{A} \mathbf{y} + \frac{1}{2} \mathbf{b}^T (\mathbf{H} - \mathbf{D}) \mathbf{b} + \frac{1}{2} \mathbf{b}^T \mathbf{D} \mathbf{b} \right] \quad (14)
 \end{aligned}$$

where $\mathbf{H} = \mathbf{A} \mathbf{R} \mathbf{A}$ and $\mathbf{D} = \text{diag}(\mathbf{H})$.

Because $\mathbf{b}^T \mathbf{D} \mathbf{b} = \text{trace}(\mathbf{D})$ for any $\mathbf{b} \in [-1, +1]^{KP}$, the (14) can be rewritten as follows:

$$\begin{aligned}
 \hat{\mathbf{b}}^{\text{ML}} &= \arg \min_{\mathbf{b} \in [-1, +1]^{KP}} \left[-\mathbf{b}^T \mathbf{A} \mathbf{y} + \frac{1}{2} \mathbf{b}^T (\mathbf{H} - \mathbf{D}) \mathbf{b} \right. \\
 &\quad \left. + \frac{1}{2} \text{trace}(\mathbf{D}) \right] \\
 &= \arg \min_{\mathbf{b} \in [-1, +1]^{KP}} \left[-\mathbf{b}^T \mathbf{A} \mathbf{y} + \frac{1}{2} \mathbf{b}^T (\mathbf{H} - \mathbf{D}) \mathbf{b} \right]. \quad (15)
 \end{aligned}$$

Comparing (13) with (15), we can obtain relationships that are shown as follows:

$$\begin{aligned}
 N &= KP, \\
 \mathbf{V} &= -\mathbf{A} \mathbf{y}, \\
 \mathbf{W} &= -\{\mathbf{H} - \mathbf{D}\}, \\
 \mathbf{b}^{\text{HNN}} &= \lim_{m \rightarrow \infty} \mathbf{X}(m). \quad (16)
 \end{aligned}$$

Hence, we can apply (16) to build the HNN detector in DS-UWB systems. The computational complexities of these are lower than ML detector due to iterative method. The structure of HNN detector is shown in Fig. 1

4 Simulation Results

Based on Intel UWB channel extensive measurements

in an indoor environment, UWB systems appear with four typical channel characteristics in an indoor environment (e.g. channel model 1(CM1), CM2, CM3 and CM4). The model parameters were found by experiment to match different UWB channel characteristics [21]. CM1 is light-of-sine (LOS) and the transmission distance is between 0 and 4 meters; CM2 is non-light-of-sine (NLOS) and transmission distance is between 0 and 4 meters; CM3 is NLOS and transmission distance is between 4 and 10 meters; CM4 is NLOS and transmission distance is more than 10 meters. The sampling time of four channel models are 2ns. Fig. 2, Fig. 3, Fig. 4, and Fig. 5 show the discrete time channel model with 2ns sampling time in CM1, CM2, CM3, and CM4, respectively.

Then, we compare the performance of three different detections: MMSE, ML, and HNN by extensive simulations of the synchronous 10-users DS-UWB systems. In order to solve multipath effect, we employ the all Rake receiver to collect the energy of all paths for DS-UWB systems for system simulation. In addition, we assume that the packet size is 4 bits and the number of user is 10 in DS-UWB systems. In Fig. 6 the MSE of HNN detector in CM1 and SNR=10dB is depicted. The HNN detector would converge after 130 iterations. In Fig. 7, Fig. 8, Fig. 9, and Fig. 10, the simulation results of BER in DS-UWB systems that employ MMSE, ML, and HNN detectors are depicted in CM1, CM2, CM3, and CM4, respectively. In these figures, the ML detector can achieve optimum than other multiuser detectors such as MMSE and HNN, but its computational complexity which grows exponentially with the number of the users forbids application in real system. In general, the optimum \mathbf{b} must be selected from 2^{KP} patterns. The MMSE detector is suboptimal, but received amplitude and noise must be known. Besides, its $(\mathbf{R} + \sigma^2 \mathbf{A}^{-2})^{-1}$ is difficult to be complemented on hardware. The performance of HNN-based detector in DS-UWB systems is better with the increase of iteration. However, the performance improvement is no longer obvious when it achieves about 130 iterations. That is because the HNN detector has many local minimum, but it is unable to determine which minimum is the global minimum. The HNN detector can waste fewer multiplications and adds to approach the performance of ML detector.

5 Conclusion

This paper demonstrated the HNN detector in DS-UWB systems. First, the common multiuser detectors such as MMSE and ML are applied to the

DS-UWB system. The optimal detector is the ML algorithm, but its complexity is higher. Although the performance of suboptimal detector such as MMSE is good, its crosscorrelation matrix \mathbf{R} is difficult to be implemented on hardware. So, we employ the HNN detector to efficiently reduce the computational complexity of ML detector. Besides, its performance approximates to the performance of the MMSE detector. Since the HNN-based detector has many local minimum, the improvement of the performance would be constrained. Therefore, how to solve to determine which minimum is the global minimum in the HNN detector is our future research.

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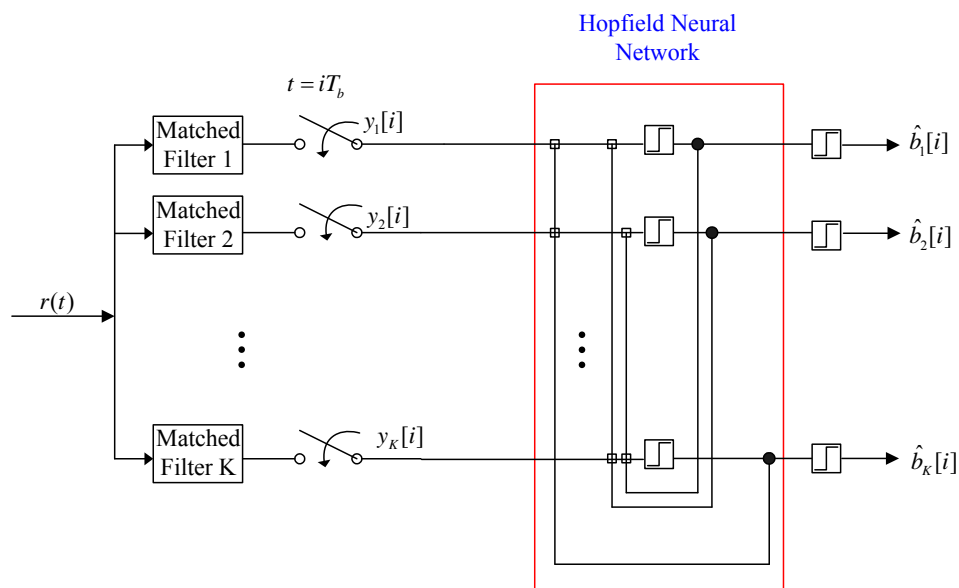


Fig. 1 The structure of HNN detector in DS-UWB Systems.

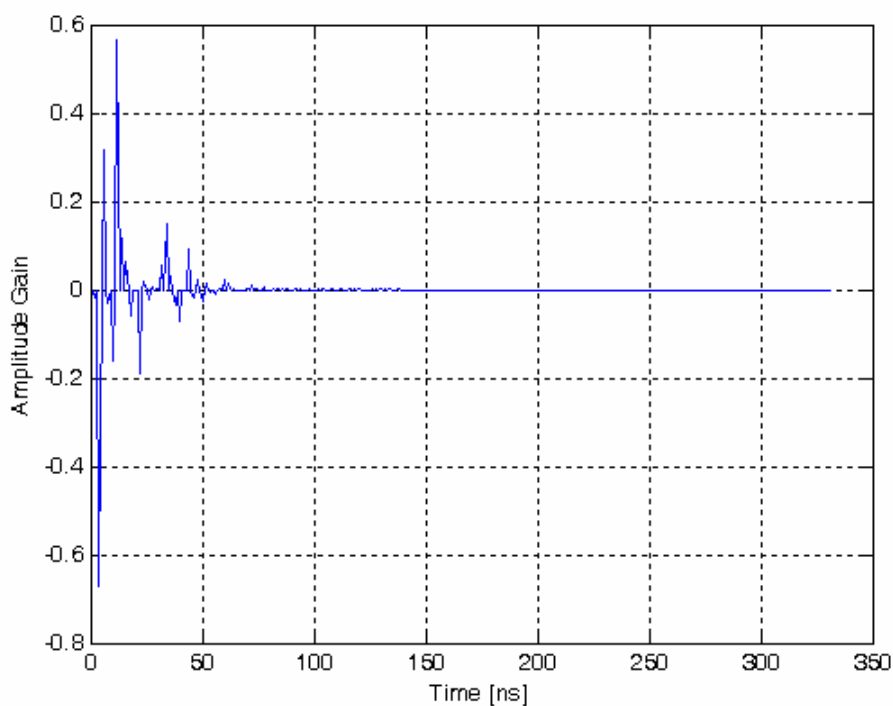


Fig. 2 Discrete time impulse response of UWB CMI

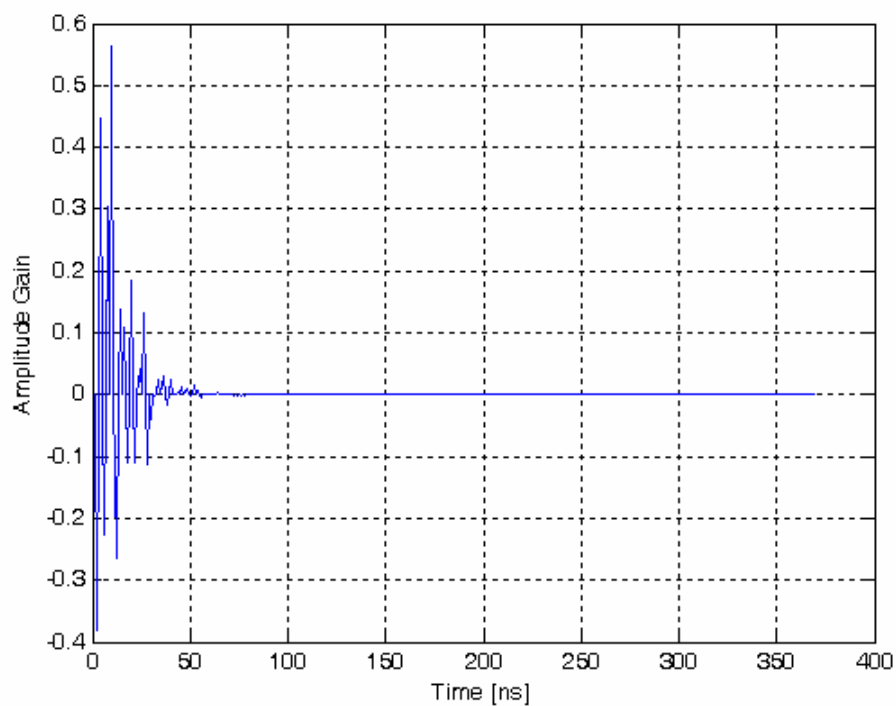


Fig. 3 Discrete time impulse response of UWB CM2

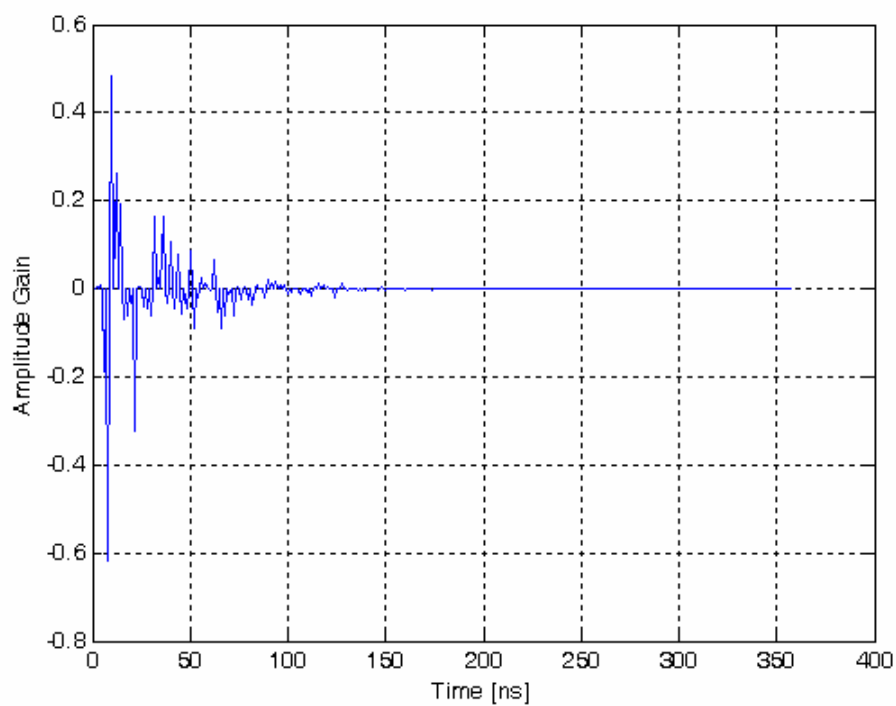


Fig. 4 Discrete time impulse response of UWB CM3

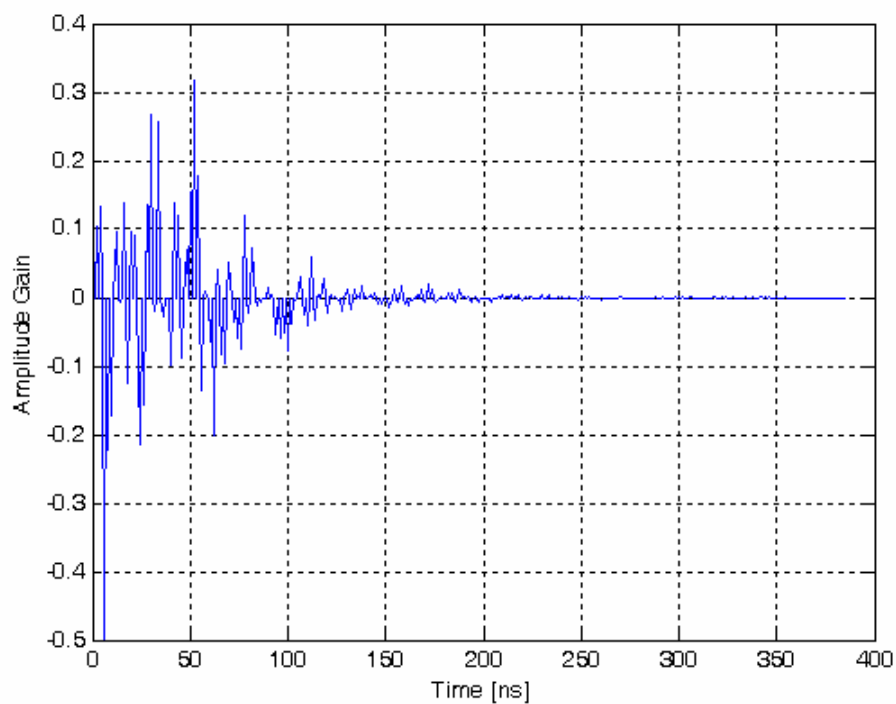


Fig. 5 Discrete time impulse response of UWB CM4

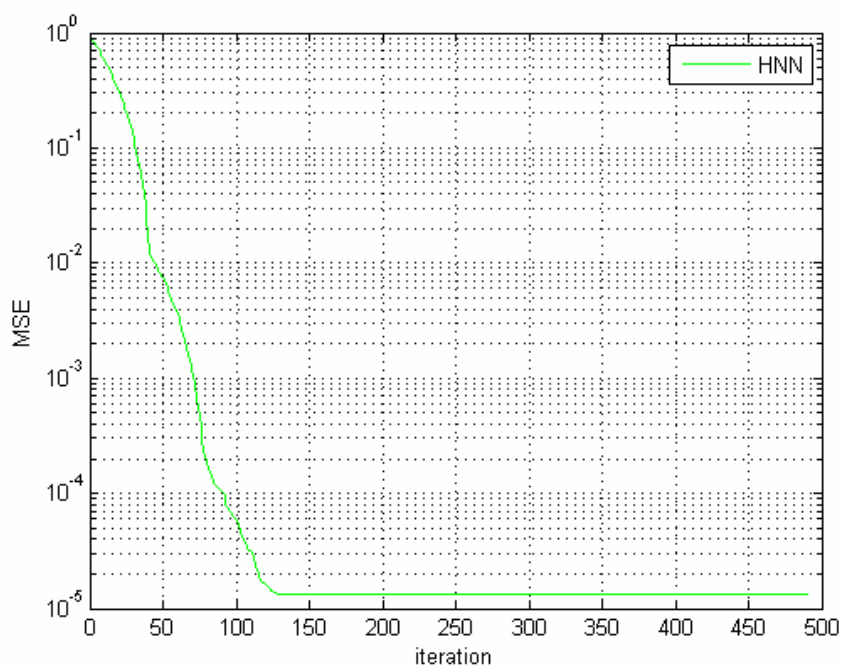


Fig. 6 The MSE of HNN detector and SNR=10dB in CM1.

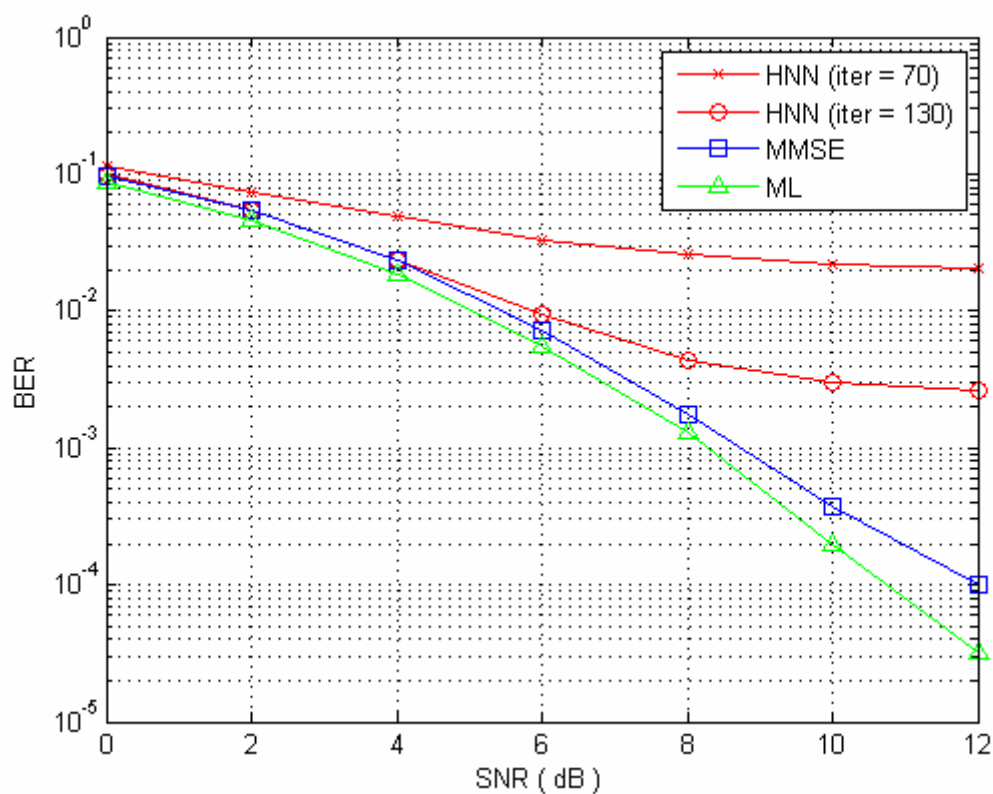


Fig. 7 The simulation of BER in DS-UWB systems that employs MMSE, ML and HNN detectors with UWB CMI.

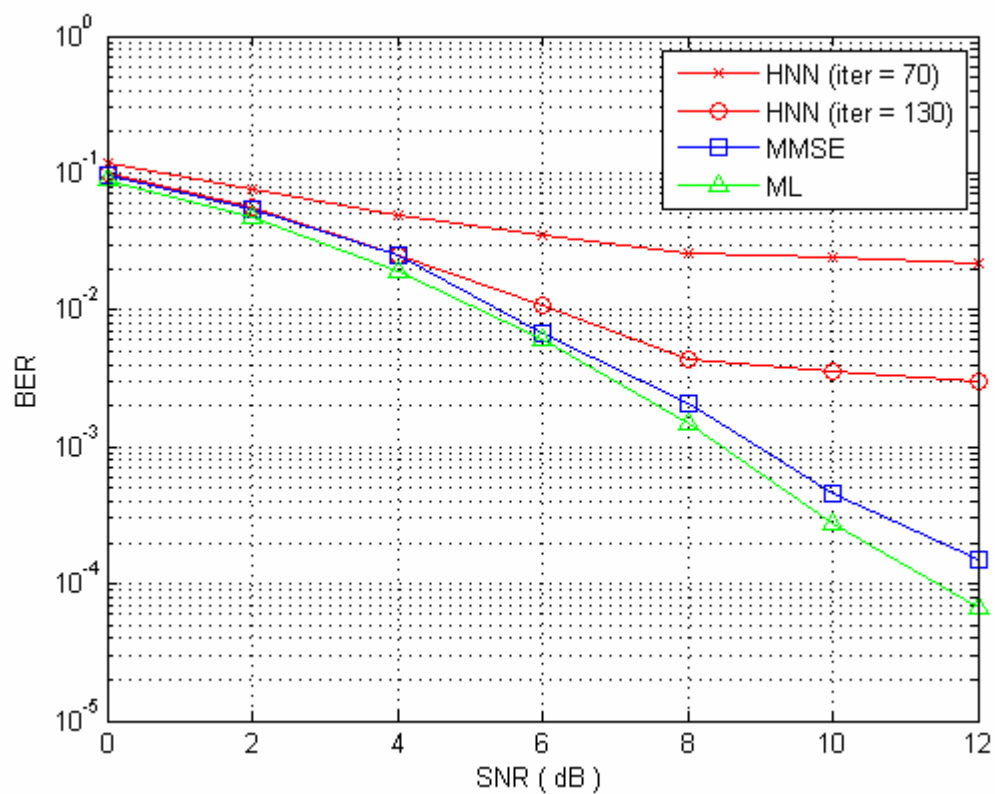


Fig. 8 The simulation of BER in DS-UWB systems that employs MMSE, ML and HNN detectors with UWB CM2.

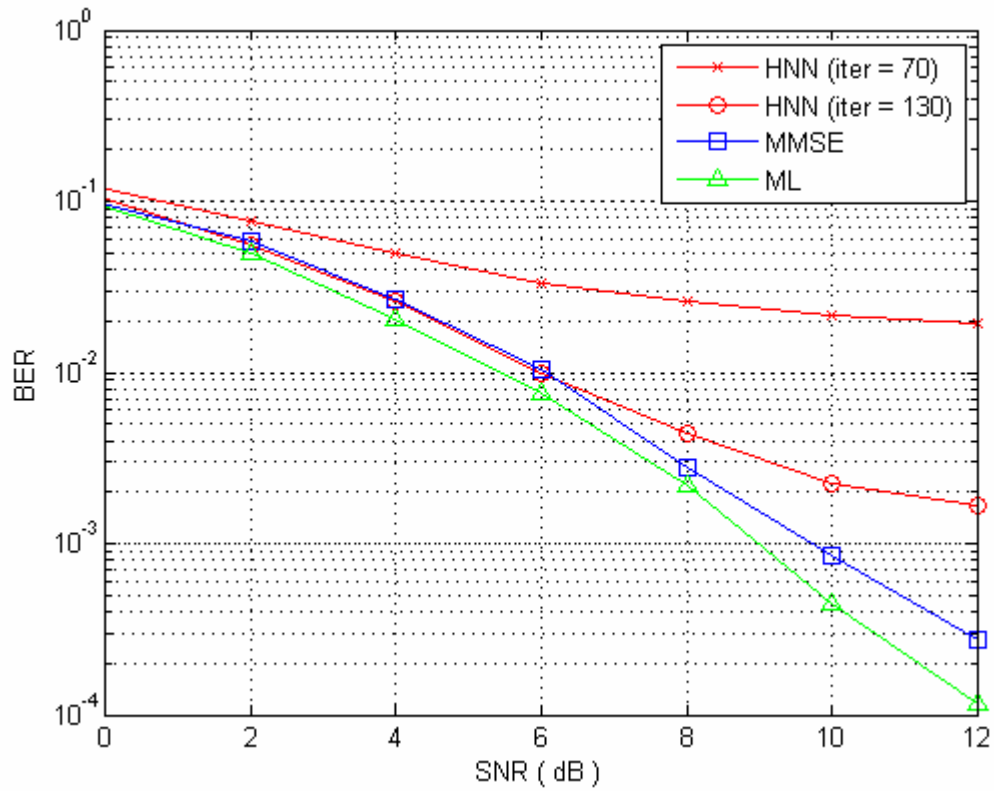


Fig. 9 The simulation of BER in DS-UWB systems that employs MMSE, ML and HNN detectors with UWB CM3.

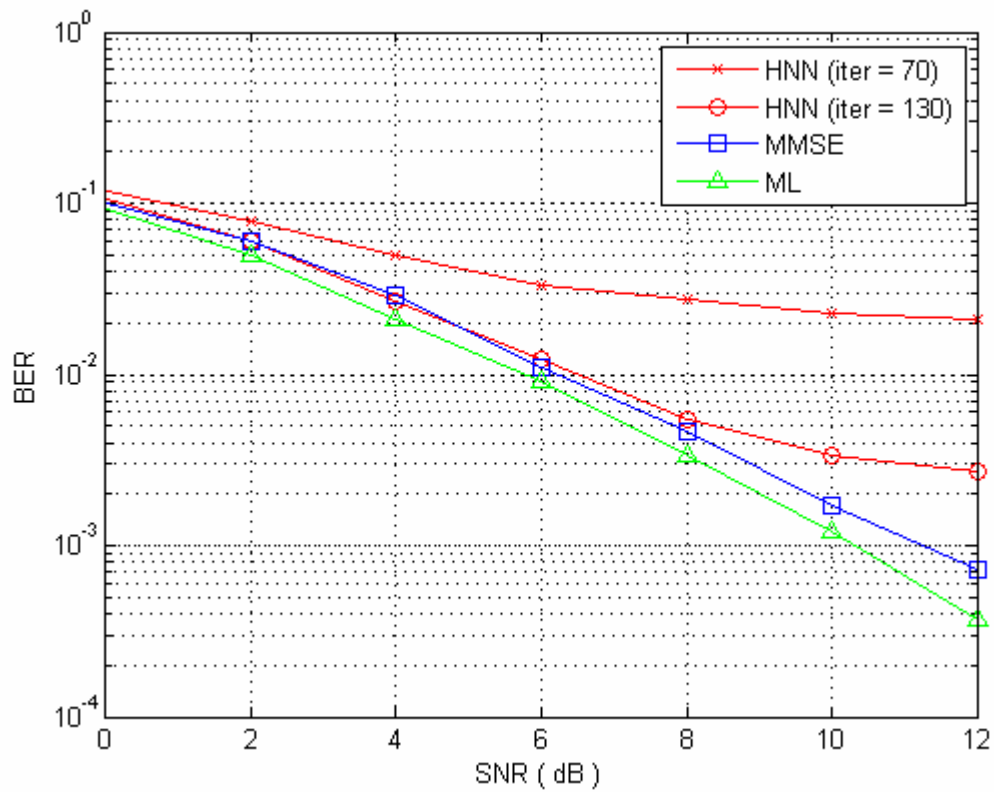


Fig. 10 The simulation of BER in DS-UWB systems that employs MMSE, ML and HNN detectors with UWB CM4.