

*Full Length Research Paper*

# Multi-user detection in ultra-wideband multiple-access communications systems using an efficient heuristic algorithm

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**This paper investigates learning and achievable bit error rate (BER) performance of ultra-wideband (UWB) systems that use intelligent multiuser detector (MUD) when communicating over UWB channels that experience both multiuser interference (MUI) and intersymbol interference (ISI), in addition to multipath fading. Multiple access interference (MAI) degrades performance of conventional single user detector in UWB systems. Due to high complexity of the optimum multiuser detector, suboptimal multiuser detectors with less complexity and reasonable performance have drawn considerable attention. By taking advantage of heuristic values and collective intelligence of tabu search with Hopfield neural networks (TAHNN), the proposed detector offers almost the same BER performance as a full-search-based optimum multiuser detector does, while greatly reducing computational complexity. To evaluate performance and robustness of our proposed TAHNN based MUD, we experiment with a number of test problems. Computational results show that our proposed TAHNN in almost all cases outperforms other foregoing heuristics applied to this paper.**

**Key words:** Ultra-wideband, Tabu search method, Hopfield neural networks, multiuser detection.

## INTRODUCTION

It is well known that multi-access interference (MAI) limits direct sequence ultra-wide band (DS-UWB) system capacity. Considering large complexity involved in optimal multiuser detection (OMUD), which is exponential in the number of active users, most current work centers on investing suboptimal approaches (Reed, 2005; Molisch et al., 2003; Scholtz, 1993; Ghavami et al., 2004; Shen et al., 2010). UWB systems offer many advantages over narrow-band or conventional wide-band system: e.g., reduced fading margins, simple transceiver designs, low probability of detection, accurate positioning (Shen et al., 2010; Ahmed et al., 2011; Oppermann et al., 2004). Traditional receiver for such a UWB system is a simple matched filter (Molisch et al., 2003; Scholtz, 1993), with

performance degraded due to MAI and intersymbol interference (ISI). Multiuser detection techniques like interference cancellation can solve the problem. OMUD (Ismail and Huseyin, 2007; Verdú, 1998; Verdú, 1986) for UWB systems requires the solution of an NP-hard combinatorial optimization problem. It is well known that computational complexity of OMUD is exponential in number of active users in the systems. Evolution of that study (Ismail and Huseyin, 2007; Verdú, 1998; Verdú, 1986) indicated OMUD possessing high-computational complexity and its implementation not viable in real time, especially when number of active users in the system becomes expressive.

To overcome these drawbacks, several advanced receiver structures have been proposed. Unlike the conventional receiver with treats MAI as if it were AWGN, multiuser receivers treat MAI as additional information to aid in detection. In order to improve the bit error ratio

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(BER) performance, multiuser detectors, such as minimum mean-square error (MMSE) MUD (Li and Rusch, 2002), may be employed by UWB systems at the expense of higher complexity. The MMSE-MUD is capable of automatically combining all multipaths presenting within time-duration of an observation window (Li and Rusch, 2002), hence it retains constant complexity. Furthermore, MMSE-MUD is convenient to implement by low-complexity adaptive techniques (Ismail and Huseyin, 2007), yielding adaptive MUD.

More researches into optimal multiuser detection for DS-UWB system multiple accesses can also be found in (Qiu et al., 2005; Foerster, 2002; Yoon and Kohno, 2002; Yihai et al., 2005; Tan-Hsu et al., 2006; Fogle, 2000) and references therein. In (Qiu et al., 2005), it is shown that it outlined design of OMUD based on joint ML sequence detection. In (Foerster, 2002), recursive multiuser detection is proposed for a direct-sequence-UWB (DS-UWB) system, which can offer near-optimal performance relative to ML detector with reduced computation complexity. Nevertheless, those approaches are similar to previous joint demodulation techniques proposed for code-division multiple-access (CDMA) and time-division multiple-access (TDMA) systems. They have very high computational complexity, which increases exponentially with total number of users. In (Yoon and Kohno, 2002), it is shown that genetic algorithm (GA) based MUD approaches single-user performance bound at lower complexity as compared with ML optimum MUD. In (Yihai et al., 2005), it is shown that each multipath component associated with a particular path collectively exhibits distortion after reflections, diffraction and scattering; thus does not resemble the ideal received signal corresponding to line-of-sight (LOS) path, which makes it difficult for practical communications receivers to fully exploit multipath diversity in a received signal. In (Tan-Hsu et al., 2006), it is shown that an approach to analyze pulse waveform dependent bit error rate performance of a DS-UWB radio working in frequency selective fading channel. It is well known that premature convergence degrades GA performance and reduces search ability (Fogle, 2000).

Analysis takes into account almost all real operational conditions: e.g., asynchronous transmissions, MAI, multipath interference, noise. In (Zi-Wei et al., 2006; Kechriotis and Manolakos, 1996; Yoon and Rao, 2000), Hopfield neural network approach (HNN) yielded better results than other conventional methods, outperforming the multistage detector; its drawback is requiring knowledge of optimal parameter values for networks. Tabu (TA) (Glover, 1989; Lee and Kang, 2000; Li et al., 2002) with a heuristic function based on matched filter outputs and ML function-controlled position mechanism has been demonstrated to achieve near-optimal BER performance in relatively low computational complexity.

This paper combines MUD and optimization techniques, MUD based on tabu learning algorithm,

which applies tabu search concept to neural network for solving optimization problems. In this paper, in order to improve BER performance of DS-UWB systems by employing conventional RAKE receivers, adaptive MUD scheme using with Hopfield neural networks technique is proposed to suppress ISI and MAI.

## METHODOLOGY

### Transmitter model

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

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

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

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

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  $T_c = T_b / N_c$ .

### Multipath channel model

The UWB indoor channel model is based on the Saleh-Valenzuela (S-V) approach (Chen et al., 2007; Karedal et al., 2004) 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  $T_c$ ,  $L_1 = L_2 = \dots = L_K = L$ , and the system is assumed to be synchronous.

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:

$$\begin{aligned}
 r(t) &= \sum_{k=1}^K q_k(t) \otimes h_k(t) + n(t) \\
 &= \sum_{k=1}^K \left[ \sqrt{E_k} \sum_{i=1}^P b_k[i] s_k(t - iT_b) \right] \otimes h_k(t) + n(t) \\
 &= \sum_{k=1}^K \sqrt{E_k} \sum_{i=1}^P b_k[i] v_k(t - iT_b) + n(t), \tag{4}
 \end{aligned}$$

where  $\otimes$  is linear convolution,  $n(t)$  is zero-mean additive white Gaussian noise and  $v_k(t) = s_k(t) \otimes h_k(t)$  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.

The template signal  $v_k(t)$  that is transmitted over a channel is corrupted by channel noise. Hence, the function of the receiver must detect the template signal  $v_k(t)$  for each user. According to (Foerster, 2002), we note that a filter which is matched to a template signal  $v_k(t)$  of duration  $(N_c+L-1)T_c$  is characterized by an impulse response. The channel response for  $k$ th user can be written as follows:

$$h_{opt,k}(t) = v_k^*(-t). \tag{5}$$

Without loss of generality, the output of the filter which is matched to a template signal  $v_k(t)$  can be written as follows:

$$\begin{aligned}
 y_k(t) &= r(t) \otimes h_{opt,k}(t) = r(t) \otimes v_k^*(-t) \\
 &= \sum_{m=1}^K \sqrt{E_m} \sum_{i=1}^P b_m[i] v_m(t - iT_b) \otimes v_k^*(-t) + n(t) \otimes v_k^*(-t), \tag{6}
 \end{aligned}$$

For our application, it is more convenient to express the associated signals in discrete-time format. Invoking Equation (6) describing the discrete-time impulse response sampling at  $t = iT_b$  is represented as follows:

$$y_k[i] = y_k(iT_b). \tag{7}$$

Then the discrete-time received signal after sampling ( $iT_b$ ) is written as follows:

$$\begin{aligned}
 y_k[i] &= \sum_{m=1}^K \sqrt{E_m} \sum_{j=1}^P b_m[j] v_m[i-j] \otimes v_k^*[-i] + n[i] \otimes v_k^*[-i] \\
 &= \sum_{m=1}^K \sqrt{E_m} \sum_{j=1}^P b_m[j] R_{m,k}[i,j] + \tilde{n}_k[i]
 \end{aligned}$$

$$= \sqrt{E_k} b_k[i] R_{k,k}[i,i] + \sqrt{E_k} \sum_{\substack{j=1 \\ j \neq i}}^P b_k[i] R_{k,k}[i,j] + \sum_{\substack{m=1 \\ m \neq k}}^K \sqrt{E_m} \sum_{j=1}^P b_m[j] R_{m,k}[i,j] + \tilde{n}_k[i], \tag{8}$$

Where

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

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

Hence, the signal that received by a conventional detection (CD) can be detected:

$$\hat{b}_k^{CD}[i] = \text{sgn } y_k[i], \tag{9}$$

Each filter is matched to one of the signature waveform. In a direct-sequence (DS) spread spectrum system where all users employ the same chip waveform, the continuous-time-to-discrete-time conversion of the bank of  $K$  matched filters can be implemented by a single chip-matched filter. In our DS-UWB systems, we consider a synchronous system; all users adopt the same packet length and chip waveform. Hence, the output vector of the bank of  $K$  matched filter outputs (Ghavami et al., 2004; Ismail and Huseyin, 2007; Verdú, 1998; Verdú, 1986) can be written as follows:

$$\mathbf{y} = \mathbf{R}\mathbf{A}\mathbf{b} + \tilde{\mathbf{n}}, \tag{10}$$

where  $\mathbf{y}$  is the received signal vector,  $\mathbf{R}$  is the cross-correlation matrix which is  $KP \times KP$  dimensional matrix,  $\mathbf{A}$  is the transmitted amplitude matrix with  $KP \times KP$  dimension,  $\mathbf{b}$  is transmitted bit vector with  $KP \times 1$  dimension and  $\tilde{\mathbf{n}}$  is a Gaussian random variable vector with zero-mean and covariance matrix  $\sigma^2 \mathbf{R}$ . Their expressions are formulated as follows:

$$\begin{aligned}
 \mathbf{A} &= \text{diag } \sqrt{E_1}, \dots, \sqrt{E_K}, \sqrt{E_1}, \dots, \sqrt{E_K}, \dots, \sqrt{E_1}, \dots, \sqrt{E_K} \\
 \mathbf{y} &= [y_1[1], y_2[1], \dots, y_K[1], y_1[2], y_2[2], \dots, y_{K-1}[P], y_K[P]]^T \\
 \mathbf{b} &= [b_1[1], b_2[1], \dots, b_K[1], b_1[2], b_2[2], \dots, b_{K-1}[P], b_K[P]]^T \\
 \tilde{\mathbf{n}} &= [\tilde{n}_1[1], \tilde{n}_2[1], \dots, \tilde{n}_K[1], \tilde{n}_1[2], \tilde{n}_2[2], \dots, \tilde{n}_{K-1}[P], \tilde{n}_K[P]]^T \\
 \mathbf{R} &= \begin{bmatrix} \mathbf{R}[1,1] & \mathbf{R}[1,2] & \dots & \mathbf{R}[1,P] \\ \mathbf{R}[2,1] & \mathbf{R}[2,2] & \dots & \mathbf{R}[2,P] \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{R}[P,1] & \mathbf{R}[P,2] & \dots & \mathbf{R}[P,P] \end{bmatrix},
 \end{aligned}$$

and

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

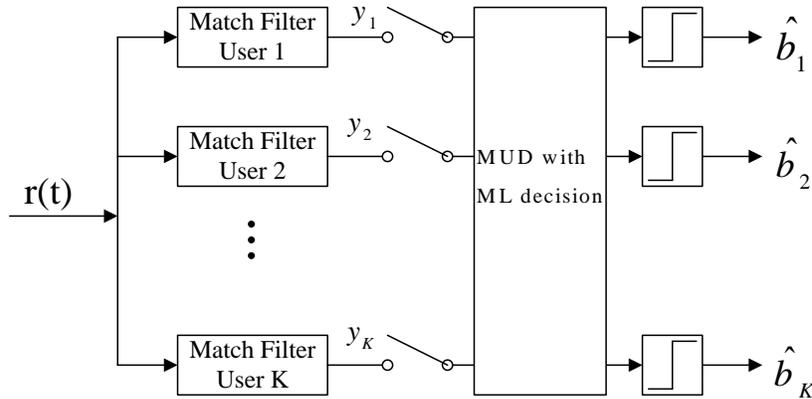


Figure 1. The structure of ML detector for DS-UWB systems.

where  $\mathbf{R}[i, j]$  is a  $K \times K$  dimensional matrix. In our DS-UWB systems, we assume that the crosscorrelation matrix  $\mathbf{R}$  is invertible. The decorrelating detectors (DD) apply the matrix  $\mathbf{R}^{-1}$  to the output of the matched filter:

$$\hat{\mathbf{b}}^{\text{DD}} = \text{sgn } \mathbf{R}^{-1} \mathbf{y} , \quad (11)$$

In order to reduce the effects of noise enhancement in the DD, the minimum mean square error (MMSE) detector were proposed in (Shen et al., 2010). Due to the fact that the MMSE detector takes background noise into account, it balances the trade-off between reducing multiple access interference and minimizing noise in the detector output. Its formula is written as follows:

$$\hat{\mathbf{b}}^{\text{MMSE}} = \text{sgn } \mathbf{R} + \sigma^2 \mathbf{A}^{-2} \mathbf{A}^{-1} \mathbf{y} . \quad (12)$$

In fact, the DD is one case of the MMSE detector. If we let  $\sigma \rightarrow 0$ , then  $(\mathbf{R} + \sigma^2 \mathbf{A}^{-2})^{-1} \rightarrow \mathbf{R}^{-1}$ . Therefore, as the signal-to-noise ratios (SNR)  $\mathbf{A}^2 / \sigma^2$  go to infinity, the performance of BER for DS-UWB systems that employs MMSE detector is approximated to the DD (Shen et al., 2010).

### Maximum likelihood detector

In this section we will derive the joint optimum decision rule for a  $K$ -user UWB system based on the synchronous model. Specifically, we want to maximize the probability of jointly correct decision of  $K$  users supported by the system based the received signal of Equation (10). From Equation (10) we note that there are  $m = 2^K$  possible combinations of  $\mathbf{b}$ . we shall denote the  $k$ th combination as  $\mathbf{b}_k$  and the combined transmit signal of all users in Equation (10) corresponding to the  $k$ th combination as  $\mathbf{b}_k \leftrightarrow \mathbf{q}_k(t)$ . Based on the notations, we can express the joint maximum a posteriori (MAP) probability criterion as (Ismail and Huseyin, 2007; Verdú, 1998; Verdú, 1986):

$$\hat{\mathbf{b}} = \arg \max_{\mathbf{b}_k} [P(\mathbf{q}_k(t) | \mathbf{y}(t))] \quad (13)$$

where  $\hat{\mathbf{b}}$  denotes the detected bit combination. Using Bayes's theorem, the a posteriori probability expression of Equation (13) can be written as (Verdú, 1998; Verdú, 1986):

$$P(\mathbf{q}_k(t) | \mathbf{y}(t)) = \frac{p(\mathbf{y}(t) | \mathbf{q}_k(t)) P(\mathbf{q}_k(t))}{p(\mathbf{y}(t))} \quad (14)$$

Where  $p(\mathbf{y}(t) | \mathbf{q}_k(t))$  is the conditional joint probability density function of the received signal  $\mathbf{y}(t)$  in Equation (10),  $P(\mathbf{q}_k(t))$  is the a priori probability of the signal containing the  $k$ th bit combination and  $p(\mathbf{y}(t))$  is probability density function of the received signal. Since the transmitted data bits of the  $K$  users are independent, the a priori probability  $P(\mathbf{q}_k(t)) = 1/2^K$  is equal for all  $m = 2^K$  bit combinations. Furthermore, the received signal probability density function  $p(\mathbf{y}(t))$  is independent of which of the  $m = 2^K$  bit combinations is transmitted. Consequently, the decision rule based on finding the signal that maximizes  $P(\mathbf{q}_k(t) | \mathbf{y}(t))$  is equivalent to find that signal that maximized  $p(\mathbf{y}(t) | \mathbf{q}_k(t))$ . This decision criterion based on the maximum of  $p(\mathbf{y}(t) | \mathbf{q}_k(t))$  is termed as the Maximum Likelihood (ML) criterion and  $p(\mathbf{y}(t) | \mathbf{q}_k(t))$  is referred to as a likelihood function. Because the probability of  $b_k[l] = +1$  is equal to the that of  $b_k[l] = -1$ , the maximum likelihood estimation can be generalized by the MAP estimation.

For a more in-depth discussion on the MAP method, the reader is referred to (Verdú, 1998). As a result, the optimal multiuser detector that fulfils ML sequence estimation (Shen et al., 2010; Verdú, 1998) gives the best performance. However, its computational complexity which grows exponentially with the number of the users forbids application in real system. The formula of ML detector is written as follows and the detector structure is shown in Figure 1.

$$\hat{\mathbf{b}}^{\text{ML}} = \arg \max_{\mathbf{b} \in \{-1, +1\}^{KP}} [2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b}] . \quad (15)$$

**Tabu-HNN based multiuser detector for UWB detector**

**Tabu search method**

The roots of Tabu search go back to the Glover's work in the 1989 (Glover, 1989). Tabu search is an iterative improvement procedure that starts from some initial feasible solution and attempts to determine a better solution in the manner of a greatest descent neighborhood search algorithm. It escapes local optima by imposing restrictions, using a short-term memory of recent solutions and strategies implied from long-term memory processes, to guide the search process. In tabu search, the neighborhood, which is being used to generate a subset of neighbors from which to select the next solution/move, is modified by classifying some moves as tabu, others as desirable. This is the key element of tabu search and is called tabu list management. In other words, tabu list management concerns updating the tabu list, i.e. deciding on how many and which moves have to be set tabu within any iteration of the search. The tabu search can see the basic components of the tabu search are the moves, tabu list and aspiration level. It is thus a metaheuristic to solve global optimization problems, based on multi-level memory management and response exploration. It requires the concept of a neighbourhood for a trial solution.

**The Hopfield neural network based multiuser detector**

In this section, the Hopfield Neural Network (HNN) algorithm (Zi-Wei et al., 2006; Kechriotis and Manolakos, 1996; Yoon and Rao, 2000; Hopfield, 1982) is introduced and applied to multiuser detection for DS-UWB systems. The HNN algorithm is one case of the neural network. The neural network consisting of hardware and software is a parallel computing system, and it employs a large number of artificial neurons to simulate the ability of biological nerve network. The neural network can be divided into recurrent network and feed-forward network. A representative recurrent network is the Hopfield network, and the feed-forward network is the back-propagation network. In general, the neural network has some advantages such as parallel processing, wrong tolerance, associate memory, VLSI implementation and optimization. However, the neural network has a serious weakness. It has many local minimums, but it is unable to determine which minimum is the global minimum. The Hopfield network that is a kind of single layer and symmetric network can be used to deal mainly with the problem of the associative memories. Hopfield employed a viewpoint of energy state of statistical mechanics to explain a phenomenon of memory. The variation of states causes the variation of energies. Hence, the training of network can reduce energy to achieve a stable state. Since the Hopfield network can be modeled as an electronic circuit, it can easily be implemented on hardware.

The network model proposed by Hopfield in 1982 was a discrete type, and all outputs of Hopfield Network were activated at either +1 or -1. Besides, the discrete Hopfield network has two updating: synchronous and asynchronous. The synchronous updating converges fast than asynchronous updating, but the performance of synchronous updating is worse than that of asynchronous updating. Therefore, we applied the discrete Hopfield network with asynchronous updating to perform multiuser detection for DS-UWB systems. 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 Hopfield network is also called Hopfield neural network (HNN).

The typical HNN algorithm with  $N$  neurons is formulated as follows:

$$X_l(m) = \text{sign } U_l$$

$$= \text{sign} \left\{ \sum_{j=1}^N W_{l,j} X_j(m-1) - V_l \right\}, \tag{16}$$

where  $W_{lj}$  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 sign { } is sign activation. The typical HNN is also named HNN. The connection weights of HNN have the following restrictions:

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

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

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 used, the network may exhibit chaotic behavior.

Besides, we apply hyperbolic tangent activation to HNN that is named tanh HNN and its algorithm is written as follows:

$$X_l(m) = \tanh U_l$$

$$= \tanh \left\{ \sum_{j=1}^N W_{l,j} X_j(m-1) - V_l \right\}, \tag{17}$$

where  $X_l(m)$  that is the output of  $l$ th neuron at the  $m$ th iteration has the range  $-1 < X_l(m) < 1$ .

In order to understand the process of HNN, we must analyze it by the viewpoint of energy. This viewpoint is from Lyapunov function (Zi-Wei et al., 2006; Kechriotis and Manolakos, 1996; Yoon and Rao, 2000; Hopfield, 1982). 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:

$$E(m) = -\frac{1}{2} \sum_{l=1}^N \sum_{j=1}^N W_{l,j} X_l(m) X_j(m) + \sum_{l=1}^N V_l X_l(m), \tag{18}$$

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.

We assume that the output of the  $l$ th neuron at time  $(m+1)$  changes and then the variation of that is written as follows:

$$\Delta X_l(m) = X_l(m+1) - X_l(m). \tag{19}$$

Due to the  $\Delta X_l(m)$ , the energy at time  $(m+1)$  becomes

$$E_l(m+1) = \left[ -\frac{1}{2} \sum_{\substack{l=1 \\ l \neq i}}^N \sum_{\substack{j=1 \\ j \neq i}}^N W_{j,l} X_l(m) X_j(m) + \sum_{\substack{l=1 \\ l \neq i}}^N V_l X_l(m) \right]$$

$$-\frac{1}{2} \sum_{j=1}^N W_{i,j} X_i(m+1) X_j(m) - \frac{1}{2} \sum_{l=1}^N W_{l,i} X_l(m) X_i(m+1) + V_i X_i(m+1). \quad (20)$$

Hence, the variation of network energy due to the variation of  $l$ th neuron is written as follows:

$$\begin{aligned} \Delta E_l(m) &= E_l(m+1) - E(m) \\ &= -\frac{1}{2} \sum_{\substack{j=1 \\ j \neq i}}^N W_{i,j} \left[ X_i(m+1) X_j(m) - X_i(m) X_j(m) \right] \\ &\quad -\frac{1}{2} \sum_{\substack{l=1 \\ l \neq i}}^N W_{l,i} \left[ X_l(m) X_i(m+1) - X_l(m) X_i(m) \right] \\ &\quad + V_i \left[ X_i(m+1) - X_i(m) \right] \\ &= -\sum_{\substack{j=1 \\ j \neq i}}^N W_{i,j} \left[ X_i(m+1) X_j(m) - X_i(m) X_j(m) \right] \\ &\quad + V_i \left[ X_i(m+1) - X_i(m) \right] \\ &= -\left[ X_i(m+1) - X_i(m) \right] \cdot \left[ \sum_{\substack{j=1 \\ j \neq i}}^N W_{i,j} X_j(m) - V_i \right] \\ &= -\Delta X_i(m) \cdot \left[ \sum_{\substack{j=1 \\ j \neq i}}^N W_{i,j} X_j(m) - V_i \right]. \quad (21) \end{aligned}$$

Because  $X_i(m)$  of discrete HNN is either +1 or -1, there are three cases to be discussed.

**Case 1:**  $\Delta E_l < 0$ :

$$\Delta X_i(m) = 2 \text{ when } \sum_{j=1, j \neq i}^N W_{i,j} X_j(m) - V_i > 0, \text{ or}$$

$$\Delta X_i(m) = -2 \text{ when } \sum_{j=1, j \neq i}^N W_{i,j} X_j(m) - V_i < 0.$$

**Case 2:**  $\Delta E_l > 0$ :

$$\Delta X_i(m) = 2 \text{ when } \sum_{j=1, j \neq i}^N W_{i,j} X_j(m) - V_i < 0, \text{ or}$$

$$\Delta X_i(m) = -2 \text{ when } \sum_{j=1, j \neq i}^N W_{i,j} X_j(m) - V_i > 0.$$

**Case 3:**  $\Delta E_l = 0$ :

$$\text{If } \Delta X_i(m) = 0 \text{ or } \sum_{j=1, j \neq i}^N W_{i,j} X_j(m) - V_i = 0.$$

In the above cases,  $\Delta E_l < 0$  illustrates that the energy of network decreases, and  $\Delta E_l > 0$  shows that it increases. If the relationships of  $\Delta E_1 = \Delta E_2 = \dots = \Delta E_N = 0$  are formed due to  $N$  successive asynchronous iterations, then the HNN achieves local minimum of energy function (Zi-Wei et al., 2006; Kechriotis and Manolakos, 1996; Yoon and Rao, 2000).

The energy function of HNN can be rewritten by vector-matrix,

$$E(m) = -\frac{1}{2} \mathbf{X}^T(m) \mathbf{W} \mathbf{X}(m) + \mathbf{V}^T \mathbf{X}(m), \quad (22)$$

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

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

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

With  $W_{l,l} = 0$ , for  $l = 1, 2, \dots, KP$ .

#### The tanhHNN based multiuser detector

Optimum multiuser detection based on the ML decision was proposed by Verdu (Verdú, 1998; Verdú, 1986). Its performance is optimal, but its time complexity grows exponentially with number of users (Ismail and Huseyin, 2007; Verdú, 1998; Yihai et al., 2005; Tan-Hsu et al., 2006). To reduce computational complexity, we employ HNN and tanhHNN detectors that can approximate to ML detector for DS-UWB systems. Recall Equation (22), it can be rewritten as follows:

$$\hat{\mathbf{b}}^{\text{ML}} = \arg \max_{\mathbf{b} \in [-1, +1]^{KP}} \left[ 2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b} \right] \quad (23)$$

$$= \arg \max_{\mathbf{b} \in [-1, +1]^{KP}} \left[ 2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{H} \mathbf{b} \right]$$

$$= \arg \min_{\mathbf{b} \in [-1, +1]^{KP}} \left[ -2\mathbf{b}^T \mathbf{A} \mathbf{y} + \mathbf{b}^T \mathbf{H} \mathbf{b} \right]$$

$$= \arg \min_{\mathbf{b} \in [-1, +1]^{KP}} \left[ -\mathbf{b}^T \mathbf{A} \mathbf{y} + \frac{1}{2} \mathbf{b}^T \mathbf{H} \mathbf{b} \right]$$

$$= \arg \min_{\mathbf{b} \in [-1, +1]^{KP}} \left[ -\mathbf{b}^T \mathbf{A} \mathbf{y} + \frac{1}{2} \mathbf{b}^T \mathbf{H} - \mathbf{D} \mathbf{b} + \frac{1}{2} \mathbf{b}^T \mathbf{D} \mathbf{b} \right], \quad (24)$$

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 (24) can be rewritten as follows:

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

$$= \arg \min_{\mathbf{b} \in [-1,+1]^{KP}} \left[ -\mathbf{b}^T \mathbf{A} \mathbf{y} + \frac{1}{2} \mathbf{b}^T \mathbf{H} - \mathbf{D} \mathbf{b} \right], \quad (25)$$

Comparing Equation (23) with Equation (25), we obtain these relationships:

$$\begin{aligned} N &= KP, \\ \mathbf{V} &= -\mathbf{A} \mathbf{y}, \\ \mathbf{W} &= -\mathbf{H} - \mathbf{D}, \\ \mathbf{b}^{HNN} &= \lim_{m \rightarrow \infty} \mathbf{X}(m). \end{aligned} \quad (26)$$

Hence, we apply Equation (26) to build HNN and tanhHNN detectors for DS-UWB systems. Computational complexity of these is lower than ML detector due to iterative method.

**Implementing Tabu-HNN based multiuser detector**

TA schemes developed for multiuser detection in code-division multiple-access (CDMA) communication, (Lee and Kang, 2000; Li et al., 2002) require knowledge of multipath channel. Yet focus on interference cancellation receiver depicted in recent works of UWB transmission has slightly differed from that in CDMA systems. In this paper, TA algorithms can also be used in UWB system as suboptimal detectors in multiuser detection, with length of tour in MUD related to objective function of ML. However, TAHNN algorithms have never been applied to the multiuser detection in DS-UWB system.

It is shown that the problem of minimizing objective function of OMD can be translated into minimizing energy function of neural network is given by (Li et al., 2002; Hopfield, 1982).

$$E_0 = \frac{1}{2} \mathbf{V}^T (\mathbf{H} - \mathbf{E}) \mathbf{V} - \mathbf{y}^T \mathbf{V} \quad (27)$$

where  $\mathbf{V}^T \mathbf{E} \mathbf{V}$  is always a positive constant number and  $\mathbf{E}$  the identity matrix. To compensate for this effect, we may simply follow approach similar to (Li et al., 2002), to obtain the TAHNN algorithm.

In Tabu search algorithm, energy surface  $E_0$  is continuously increased in a neighborhood of the current state. At time  $t$ , energy surface is given by

$$E_t = E_0 + F_t(\mathbf{V}) \quad (28)$$

Where  $F_t(\mathbf{V}) = \beta \int_0^t e^{\alpha(s-t)} P(\mathbf{V}, \mathbf{V}(s)) ds$ , with scalars  $\alpha$  and  $\beta$  as positive constants and  $P(\mathbf{V}, \mathbf{W})$  measuring vectors  $\mathbf{V}$  and  $\mathbf{W}$  proximity. This paper selects quadratic proximity function given by (Li et al., 2002; Soujeri and Bilgekul, 2002)

$$P(\mathbf{V}, \mathbf{W}) = \frac{1}{8} \sum_i \sum_{j \neq i} (1 + V_i W_i)(1 + V_j W_j) \quad (29)$$

Then the neural network that performs gradient descent on  $E_t$  has the state equation

$$L_i \dot{u}_i = -\frac{1}{R_i} u_i + \sum_j T_{ij} + S_{ij} V_j + y_i + J_i \quad (30)$$

where  $T = -(\mathbf{H} - \mathbf{E})$ ,  $S_{ii} = 0$  and  $S_{ij}(t)(i \neq j)$  and  $J_i(t)$  satisfy this definition:

$$\begin{aligned} \dot{S}_{ij} &= -\alpha S_{ij} - \frac{\beta}{4} V_i V_j, \\ \dot{J}_i &= -\alpha J_i - \frac{\beta}{4} (K - 1) V_i \\ V_i &= \text{sign}(u_i) \end{aligned} \quad (31)$$

Basic procedure used in TAHNN search algorithm to find minimum total cost route can be summarized in the following steps:

**Step 1:** At the beginning of TAHNN search process, starting point is chosen by the random selection in feasible solution space and sent to HNN for optimization process. Tabu search algorithm has global searching ability and is used to provide initial point for HNN. In this paper, the first individual of TAHNN algorithm may be randomly initialized, but preliminary simulations showed initialization with outputs of RAKE receivers both improving the best found solution and reducing computational load.

**Step 2:** To find the neighborhood solution, next starting point is selected and sent to HNN again to obtain better result accordingly. Vector from previous to new starting point is stored in memory.

**Step 3:** New result is compared with the best one among previous searches. If the new one is better than the best in memory, it replaces the old one; if not, the new one is added to the Tabu list on the condition that it is not the best one among the Tabu list.

**Step 4:** In case the last search result proved best, next starting point is selected toward previous search direction, using vector in Step 2, and the search procedure is repeated from Step 2. If the last result was not the best, new starting point is selected randomly, and the procedure also goes to Step 2.

**Complexity issues**

In this subsection, we give a brief description of the computational complexity of the proposed TAHNN multiuser detector. As we known, in full-complexity ML MUD scheme, calculation of the object function-equation (13) for all possible data vector  $\mathbf{b}$  results an exhaustive search complexity which increases exponentially with  $K$ .

Hence, the computational complexity is  $O(K2^K)$  per bit per iteration (Verdú, 1998; Verdú, 1986). Clearly, the complexity is prohibitive for heavy loaded system with large number of users. The

computational complexity of detecting  $K$  bits in DD is of order  $K^2$ . The computational complexity/bit of the suboptimum DD and MMSE detector is linear with  $K$  on the order of  $O(K)$  (Scholtz, 1993; Ghavami et al., 2004). The computational complexity of TAHNN-based MUD can be significantly reduced by employing a candidate list. In this way, the complexity turns to be proportional with the cardinality of the candidate list  $N_d$ . We assume a total number of

steps  $m_s$  and the number of particles in generations  $N_h$ . Thus, the computational complexity per bit per iteration of the TAHNN based MUD is then  $O(Km_s N_d)$ . It is worth noting that  $K$  fixed in certain systems which depends on the number of active users, modulation

**Table 1.** The comparisons of computational complexity for ML, HNN, tanhHNN and TAHNN detectors.

Detectors	Multiplications	Adders
ML	$2^N(2N^2+4N+1)$	$2^N(N^2+N-1)$
HNN with $M$ iterations	$M(N-1)$	$M(N-1)$
tanhHNN with $M$ iterations	$M(N-1)$	$M(N-1)$
TAHNN with $k_s$ and $m_s$	$k_s \times m_s \times (N-1)$	$k_s \times m_s \times (N-1)$

schemes and the transmit antennas. So the complexity of the TAHNN-based MUD is directly decided by  $m_s$  and  $k_s$ .  $k_s$  denotes particle population.

The idea of employing hybrid TA method comes from the fact that we can use embedded HNNs to accelerate convergence and save the search steps  $m_s$ . In general, it is possible to reduce the complexity by restricting the number of embedded HNNs to  $N_h < N_d$ . The next section will illustrate that the value of  $N_d$  can be fixed to be a small value comparing with  $N_h$ . Meanwhile, the embedded HNNs helps to reduce the number of steps  $m_s$  without a loss of performance.

According to Equation (15), we let  $N=KP$ . Hence the formula of ML detector can be rewritten as follows:

$$\hat{\mathbf{b}}^{\text{ML}} = \arg \max_{\mathbf{b} \in \{-1, +1\}^N} [2\mathbf{b}^T \mathbf{A} \mathbf{y} - \mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b}]$$

By above formula, we can compute the multiplications and adders of ML detector. The first part of Equation (15) is written as follows:

$$2\mathbf{b}^T \mathbf{A} \mathbf{y} = 2 \begin{bmatrix} b_1 & b_2 & \cdots & b_N \end{bmatrix} \begin{bmatrix} A_{1,1} & 0 & \cdots & 0 \\ 0 & A_{2,2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A_{N,N} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = 2 \sum_{i=1}^N b_i A_{i,i} y_i,$$

where term  $2\mathbf{b}^T \mathbf{A} \mathbf{y}$  wastes  $(2N+1)$  multiplications and  $(N-1)$  adders. The second part of (15) is written as follows:

$$\mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b} = \begin{bmatrix} b_1 A_{1,1} & b_2 A_{2,2} & \cdots & b_N A_{N,N} \end{bmatrix} \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,N} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ r_{N,1} & r_{N,2} & \cdots & r_{N,N} \end{bmatrix} \begin{bmatrix} b_1 A_{1,1} \\ b_2 A_{2,2} \\ \vdots \\ b_N A_{N,N} \end{bmatrix}$$

$$= \begin{bmatrix} b_1 A_{1,1} & b_2 A_{2,2} & \cdots & b_N A_{N,N} \end{bmatrix} \begin{bmatrix} \sum_{i=1}^N r_{1,i} b_i A_{i,i} \\ \sum_{i=1}^N r_{2,i} b_i A_{i,i} \\ \vdots \\ \sum_{i=1}^N r_{N,i} b_i A_{i,i} \end{bmatrix}$$

$$= b_1 A_{1,1} \sum_{i=1}^N r_{1,i} b_i A_{i,i} + b_2 A_{2,2} \sum_{i=1}^N r_{2,i} b_i A_{i,i} + \cdots + b_N A_{N,N} \sum_{i=1}^N r_{N,i} b_i A_{i,i},$$

where term  $\mathbf{b}^T \mathbf{A} \mathbf{R} \mathbf{A} \mathbf{b}$  wastes  $N(2N+2)$  multiplications and  $[N(N-1)+(N-1)]$  adders. For each pattern  $\mathbf{b}$  of ML detector, the multiplications are equal to  $2N^2+4N+1$  and adders are equal to  $N^2+N-1$ . Besides, the ML detector must compute  $2^N$  patterns. For  $2^N$  patterns, the multiplications are equal to  $2^N(2N^2+4N+1)$  and adders are equal to  $2^N(N^2+N-1)$ .

The typical HNN algorithm with  $N$  neurons is written by Equation

(16). The term  $\sum_{j=1, j \neq l}^N W_{l,j} X_j(m-1)$  of HNN algorithm wastes

$(N-1)$  multiplications and  $(N-2)$  adders. So,

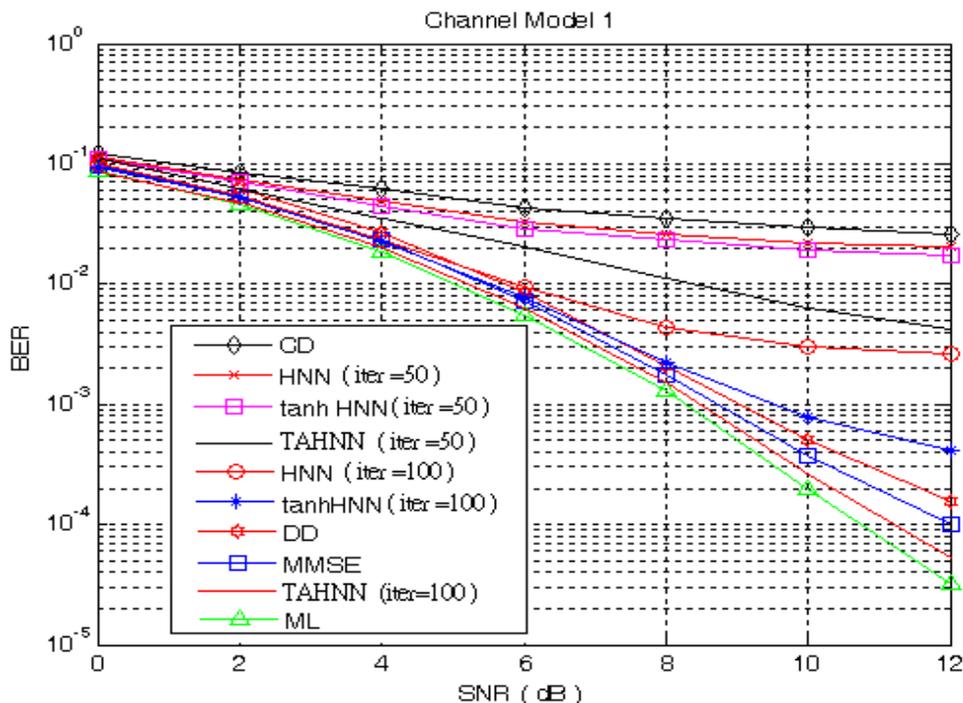
$\sum_{j=1, j \neq l}^N W_{l,j} X_j(m-1) - V_l$  wastes  $(N-1)$  multiplications and  $(N-1)$

adders. Besides, the sign activation can be complemented by OP amplifier. For  $M$  iterations of HNN detector, it wastes  $M(N-1)$  multiplications and  $M(N-1)$  adders. The tanhHNN detector is represented by Equation (17) and its activation can be implemented by OP amplifier. If we neglect the complexity of hyperbolic tangent, the operators of tanhHNN detector are equal to HNN. In our TAHNN detector, the parameters of  $k_s$  and  $m_s$  increase the iterations of tanhHNN detector. It mainly wastes  $k_s \times m_s \times (N-1)$  multiplications and  $k_s \times m_s \times (N-1)$  adders. The operators of above detectors are listed in Table 1.

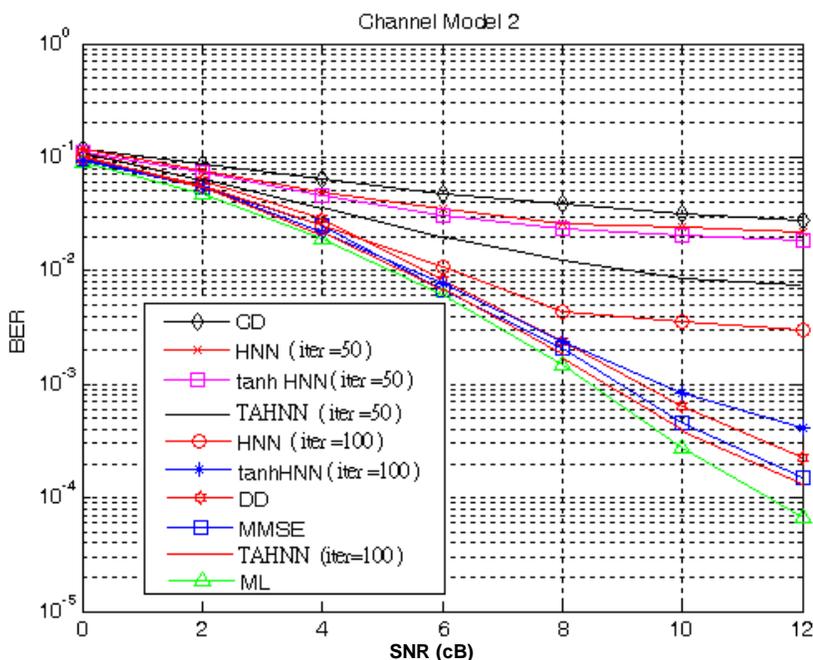
## RESULTS AND DISCUSSION

In this section we compare performance of six different detections: DD, MMSE, ML, HNN, tanhHNN and TAHNN by extensive simulations of synchronous ten-user DS-UWB systems. The UWB channel model 1-4 discussed in this paper indicate different transmission distance for indoor environment, all Rake receiver adopted for channel model 1-4. In addition, we assume packet size as four bits and the number of users as ten for DS-UWB systems. Figure 2 depicts simulation of BER for DS-UWB systems that employs DD, MMSE, ML, HNN, tanhHNN and TAHNN with UWB CM 1. Figure 2 shows HNN detectors yielding poorer performance than other detectors; ML detector performs best, but its computational complexity is high. The TAHNN detector outperforms DD, approaching MMSE detector.

Similarly, Figures 3 to 5 display UWB CM 2, CM 3 and



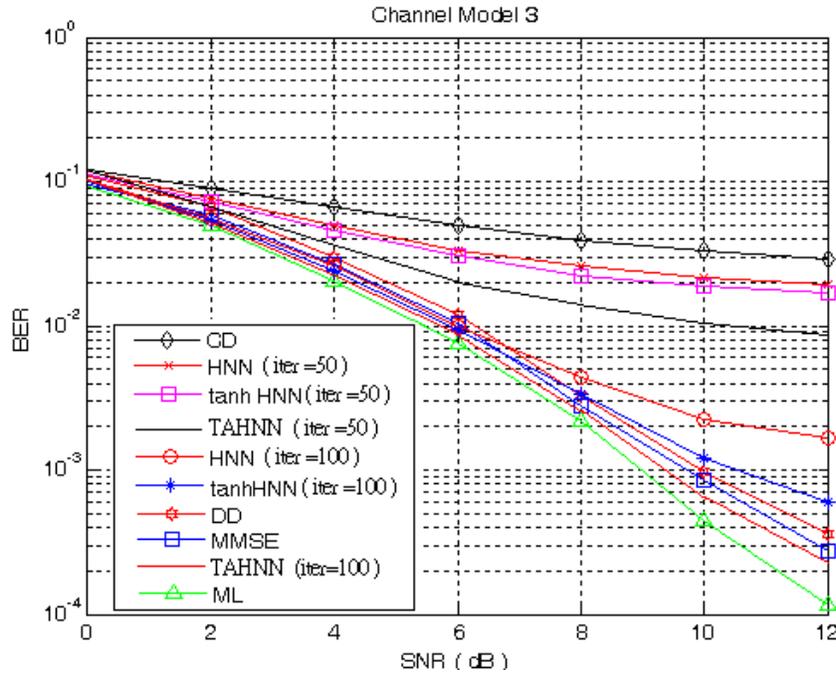
**Figure 2.** Simulation of BER for DS-UWB systems that employ CD, DD, MMSE, ML, HNN and tanhHNN detectors with UWB CM 1.



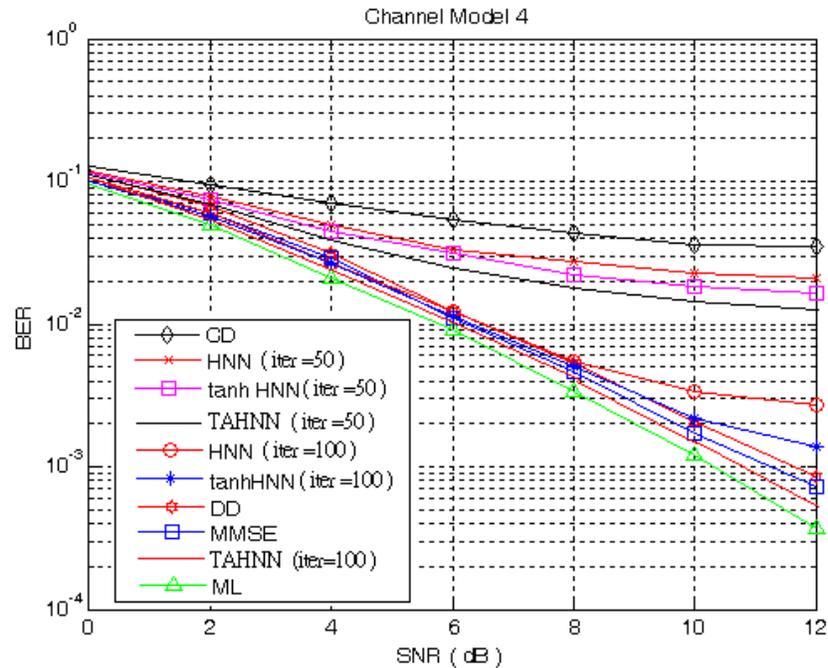
**Figure 3.** Simulation of BER for DS-UWB systems that employ CD, DD, MMSE, ML, HNN and tanhHNN detectors with UWB CM 2.

CM 4. Figure 3 shows the performance of TAHNN detector for UWB CM 2 as superior to DD, its

performance approaching that of MMSE detector. Figure 4 shows performance of TAHNN detector for UWB CM 3



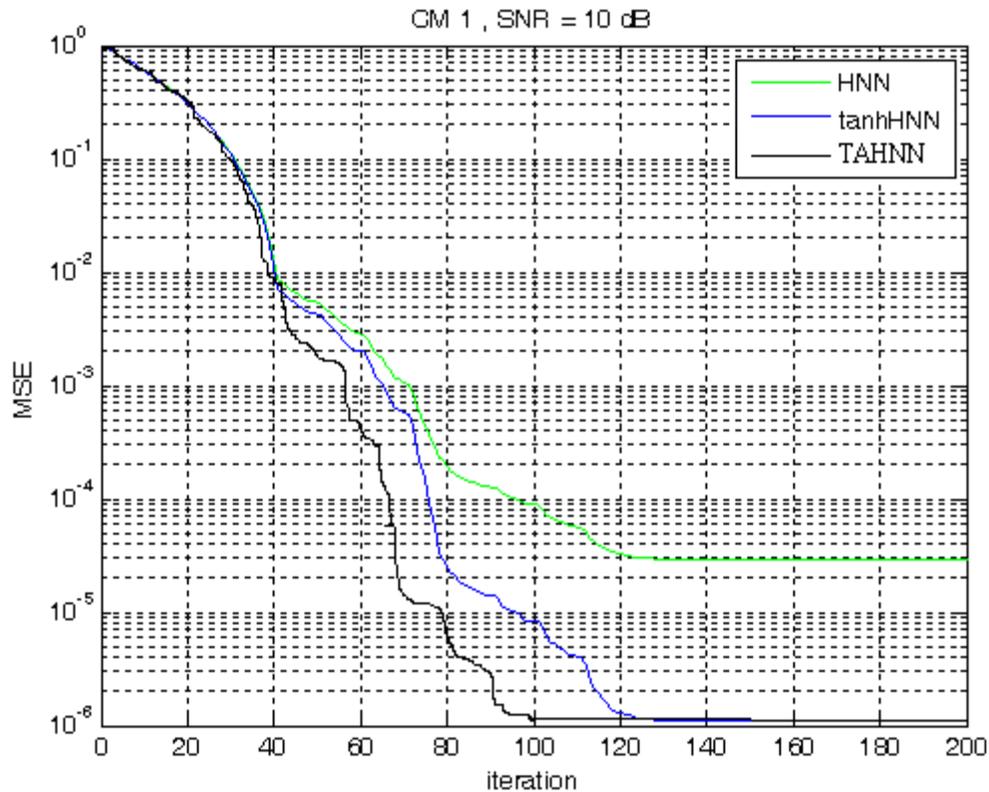
**Figure 4.** Simulation of BER for DS-UWB systems that employ CD, DD, MMSE, ML, HNN and tanhHNN detectors with UWB CM 3.



**Figure 5.** Simulation of BER for DS-UWB systems that employ CD, DD, MMSE, ML, HNN and tanhHNN detectors with UWB CM 4.

better than DD, also approaching that of MMSE detector. Figure 5 shows TAHNN detector for UWB CM 4

outperforming both DD and MMSE. The hardware of TAHNN detector resembles that of HNN; software of



**Figure 6.** MSE of TAHNN, HNN, and tanhHNN detectors.

TAHNN needs more time than HNN. This is a trade-off between performance and time. The TAHNN detector can behave as a suboptimal detector in terms of performance and time.

These figures show performance of tanhHNN detector always better than HNN detector at the same iteration. Moreover, performance of tanhHNN detector approximates DD at SNR=0-6dB for other UWB channel models, but worse at SNR=8-12dB for others. Neuron output of HNN detector with sign activation is either +1 or -1; neuron output of tanhHNN detector is distributed from -1 to +1. This is the main difference between sign and hyperbolic tangent activation. With the proposed scheme, MUD objective function is mapped on HNN energy function, a penalty section added to the energy function according to TA method, upon which solution search always tends towards states not yet visited. This procedure enables the state trajectory to climb out of local minima thereby converge toward optimal and near-optimal solution. This algorithm, justified by simulation experiments, is extremely effective due to global convergence capability together with square computation complexity. This is the original motive of our work.

Figure 6 presents convergence profiles of three investigated MUD when SNR is fixed at 7dB. From this we can see MSE of TAHNN MUD converging faster than the other MUD when iteration number is 120. Compared

with HNN multiuser detector, both TAHNN and tanhHNN multiuser detectors exhibit robust convergence profiles. Still, TAHNN multiuser detector reaches robust convergence faster than the tanhHNN multiuser detector by at one order of magnitude at 100 iterations. Moreover, HNN and tanhHNN detectors waste fewer multiplications and adds to approach performance of ML detector.

Comparing results for HNN, tanhHNN and TAHNN MUD, we see that the MSE for TAHNN MUD reduced by one and two orders of magnitude at 120 iterations. Figure 6 shows TAHNN detector outperforming others after 120 iterations, yet wasting more time than others, a trade-off in terms of performance and time.

## Conclusion

Development of heuristic MUD means TAHNN algorithm can solve MAI problems. To improve performance of the HNN problem, a hybrid method is developed in this research to combine HNN and TA together (TAHNN). Such a method affords better solution diversity and good convergence ability during evolutionary procedure. This paper presents iterative MUD based on heuristic technique for DS-UWB systems. The proposed scheme is featured as an effective TAHNN-based MUD technique greatly reducing computational complexity with minimal

penalty in performance compared with conventional MUD. Numerical results demonstrate performance of our algorithm lending better performance/complexity compromise than conventional MUDs.

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