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Genetic Algorithm based Equalizer for Ultra-Wideband Wireless Communication Systems

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1. Introduction

Ultra-wideband (UWB) systems operate in the 3.1 $\sim$ 10.6GHz spectrum allowed by the Federal Communications Commission (FCC) on an unlicensed basis. The ultrawide bandwidth and ultralow transmission power density (-41.25 dBm/MHz for indoor applications) make UWB technology attractive for high-speed, short-range (e.g.,indoor) wireless communications Cai et al. (2006). UWB signal generations for the high-speed, short-range networking is in support of a variety of potential low-cost, low-power multimedia transport applications in home and enterprise environments. Typical scenario is provisioning wireless data connectivity between desktop PC and associated peripherals like keyboard, mouse, printer, etc. Additional driver applications relates to streaming of digital media content between consumer electronics appliances such as TV sets, VCRs, audio CD/DVD and MP3 players Roy et al. (2004).

In an impulse-based DS-UWB system, the transmitted data bit is spread over multiple consecutive pulses of very low power density and ultra-short duration. This introduces resolvable multipath components having differential delays in the order of nanoseconds. Thus, the performance of a DS-UWB system is significantly degraded by the inter-chip interference (ICI) and inter-symbol interference (ISI) due to multipath propagation Liu & Elmirghani (2007).

In a frequency-selective fading channel, a RAKE receiver can be used to exploit multipath diversity by combining constructively the monocycles received from the resolvable paths. Maximum ratio combining (MRC)-RAKE is optimum when the disturbance to the desired signal is sourced only from additive white Gaussian noise (AWGN), therefore it has low computational complexity. However, the presence of multipath fading, ISI, and/or narrowband interference (NBI) degrades the system performance severely Sato & Ohtsuki (2005). The maximum likelihood detection (MLD) is optimal in such a frequency selective channel environment as UWB channel but its computational complexity grows exponentially with the constellation size and the number of RAKE fingers.

The high computational complexity of MLD motivates research for suboptimal receivers with reduced complexity such as linear and non-linear equalizers. In Kaligineedi & Bhargava (2006), performance of non-linear frequency domain equalization schemes viz. decision feedback equalization (DFE) and iterative DFE for DS-UWB systems were studied. Eslami et al in Eslami & Dong (2005) presented the performance of joint RAKE and minimum mean

square error (MMSE) equalizer receiver for UWB communication systems. Parihar et al in two different papers, Parihar et al. (2005) and Parihar et al. (2007) gave thorough analysis of linear and non-linear equalizers for DS-UWB systems considering two different modulation techniques, binary phase shift keying (BPSK) and 4-ary bi-orthogonal keying (4BOK).

Known channel state information (CSI) has been assumed in previous work but practically this is not feasible, because the wireless environment is always changing. Channel estimation is of particular importance in future broadband wireless networks since high data-rate transmissions lead to severe frequency-selective channel fading, which necessitates the use of channel estimation/equalization techniques to combat significant the ISI Sun & Li (2007).

Lots of research work has been done on channel estimation techniques using both the training based and blind approaches. In Sato & Ohtsuki (2005), Mielczarek et al. (2003) and Chu et al. (2008), the pilot-aided channel estimation were carried out. Sato and Ohtsuki in Sato & Ohtsuki (2005) used data-aided approach based on using known pilot symbols to estimate the channel impulse response. The sliding window (SW) and successive cancellation (SC) algorithms were proposed in Mielczarek et al. (2003). Chu et al. also proposed a pilot-channel-assisted log-likelihood-ratio selective combining (PCA-LLR-SC) scheme for UWB systems in Chu et al. (2008). In another set of data-aided approaches based on maximum likelihood (ML) scheme, Wang, Xu, Ji & Zhang (2008) proposes a ML approach to channel estimation using a data-aided simplified ML channel estimation algorithm. In Lottici et al. (2002), Lottici et al. proposed data-aided (DA) and non-data aided (NDA) scenarios based on the ML criterion. Frequency domain channel estimation were reported in Takanashi et al. (2008) where an iterative frequency domain channel estimation technique was proposed for multiple-input multiple-output (MIMO)-UWB communication systems.

The genetic algorithm (GA) works on the Darwinian principle of natural selection called "survival of the fittest". GA possesses an intrinsic flexibility and freedom to choose desirable optima according to design specifications. GA presumes that the potential solution of any problem is an individual and can be represented by a set of parameters regarded as the genes of a chromosome and can be structured by a string of values in binary form Man et al. (1999). GA is a well studied and effective search technique used in lots of work in CDMA communication systems as can be found in Erguin & Hacioglu (2000); Yen & Hanzo (2001) and Al-Sawafi (2004). In Erguin & Hacioglu (2000), a hybrid approach that employs a GA and multistage detector for the multiuser detection in CDMA system was proposed. Yen and Hanzo in Yen & Hanzo (2001) applied GA as a joint channel estimation and multiuser symbol detection in synchronous CDMA systems. A micro GA was developed in Al-Sawafi (2004) as a multiuser detection technique in CDMA system. GA has also been applied to UWB communication systems in Gezici et al. (2005); Wang et al. (2004) and Wang, Yang & Wu (2008). In Gezici et al. (2005), a GA-based iterative finger selection scheme, which depends on the direct evaluation of the objective function, was proposed. T.Wang et al in Wang et al. (2004) formulated an optimization problem aiming to reduce multiband jam interference power on UWB THSS IR system with 2-PPM which belongs to the class of nonlinear combinational optimization. UWB pulse design method was carried out in Wang, Yang & Wu (2008) using the GA optimization. However, to the best of our knowledge, no work has been done, using GA for channel equalization with pilot-aided channel estimation in DS-UWB communication systems.

In this chapter, we propose an equalization approach using GA in DS-UWB wireless communication, where GA is combined with a RAKE receiver to combat the ISI due to the frequency selective nature of UWB channels for high data rate transmission. We also compare our proposed RAKE-GA equalization approach with the MMSE based linear equalization approach and the optimal MLD approach to demonstrate a trade-off between performance

and computational complexity. Moreover, we employ a data aided approach to estimate the channel amplitudes and delays using a sliding window method, which has lower complexity than ML based channel estimation methods Sato & Ohtsuki (2005).
Simulation results show that the proposed GA based structure significantly outperforms the RAKE and RAKE-MMSE receivers. It also provides a very close bit error rate (BER) performance to the optimal RAKE-MLD approach, while requiring a much lower computational complexity. The impact of the number of RAKE fingers on the RAKE-GA algorithm and the speed of convergence in terms of the BER against the number of generations are investigated by simulation, while the number of training overhead, that is the percentage of pilot symbols size compared to the number of transmitted data, is also presented with a plot of BER against the number of training symbols.
Section 2 is the system model. We propose a RAKE-GA equalization approach in Section 3. The data-aided channel estimation for all the receivers are presented in Section 4. Section 5 presents the computational complexity of the RAKE-GA. Simulation results are shown in Section 6. Section 7 draws the conclusion.

2. System model

2.1 Transmit signal

The transmit signal for the DS-UWB can be expressed as

$$x(t) = \sqrt{E_c} \sum_{k=-\infty}^{\infty} d_k v_{\mathrm{TR}}(t - kT_s). \tag{1}$$

where the transmit pulse $v_{\mathrm{TR}}(t)$, is generated by using the ternary orthogonal code sequence as specified in the IEEE standard **?** due to its orthogonality and is of the form given in (2). E_c is the energy per transmitted pulse, $d_k \in \{\pm 1\}$ is the k^{th} transmit symbol, T_s is the interval of one symbol or frame time, each frame is subdivided into N_c equally spaced chips giving $T_s = N_c T_c$.

$$v_{\mathrm{TR}}(t) = \sum_{i=0}^{N_c-1} b_i g(t - iT_c). \tag{2}$$

where $b_i \in \{-1, 0, 1\}$ is the i^{th} component of the spreading code, T_c is the chip width, $g(t)$ represents the transmitted monocycle waveform which is normalized to have unit energy and N_c is the length of the spreading code sequence.

2.2 Channel model

According to Molisch & Foerster (2003), a reliable channel model, which captures the important characteristics of the channel, is a vital prerequisite for system design. Toward this end, the IEEE 802.15.3a task group has evaluated a number of popular indoor channel models to determine which model best fits the important characteristics from realistic channel measurements using UWB waveforms. The goal of the channel model is to capture the multipath characteristics of typical environments where IEEE 802.15.3a devices are expected to operate. The model should be relatively simple to use in order to allow PHY proposers to use the model and, in a timely manner, evaluate the performance of their PHY in typical operational environments.
A log-normal distribution rather than a Rayleigh distribution for the multipath gain magnitude is used because the log-normal distribution fits the measurement data better. In

addition, independent fading is assumed for each cluster as well as each ray within the cluster. Therefore, channel impulse response of this model expressed in a simpler form is given as:

$$h(t) = \sum_{l=1}^{L_{tot}} h_l \delta(t - \tau_l). \tag{3}$$

where L_{tot} is the total number of paths, $\tau_l (= lT_c)$ is the delay of the l^{th} path component and h_l is the l^{th} path gain Foerster (2003).

2.3 Receive signal

The receive signal $r(t)$, which is the convolution of the transmit signal in (1) with the channel impulse responses given in (3) and the addition of noise is shown in (4) as

$$r(t) = x(t) * h(t) + n(t) = \sqrt{E_c} \sum_{k=-\infty}^{\infty} d_k v_{\mathrm{TR}} \sum_{l=1}^{L_{tot}} h_l \left(t - kT_f - \tau_l\right) + n(t). \tag{4}$$

where $n(t)$ is the additive white Gaussian noise (AWGN) with zero mean and a variance of σ^2, $*$ denotes the convolution operator.

3. RAKE-GA based equalization for DS-UWB systems

In this section, we present an equalization approach for DS-UWB systems by using GA. The block diagram of the GA based equalization approach is shown in Fig. 1, where the blocks in the dashed boxing are the initialization of the GA based equalization using RAKE demodulator. The GA is then employed to equalize the output signals from the RAKE demodulator. Compared to the optimal MLD receiver, the proposed RAKE-GA receiver has much lower computational complexity and negligible performance degradation.

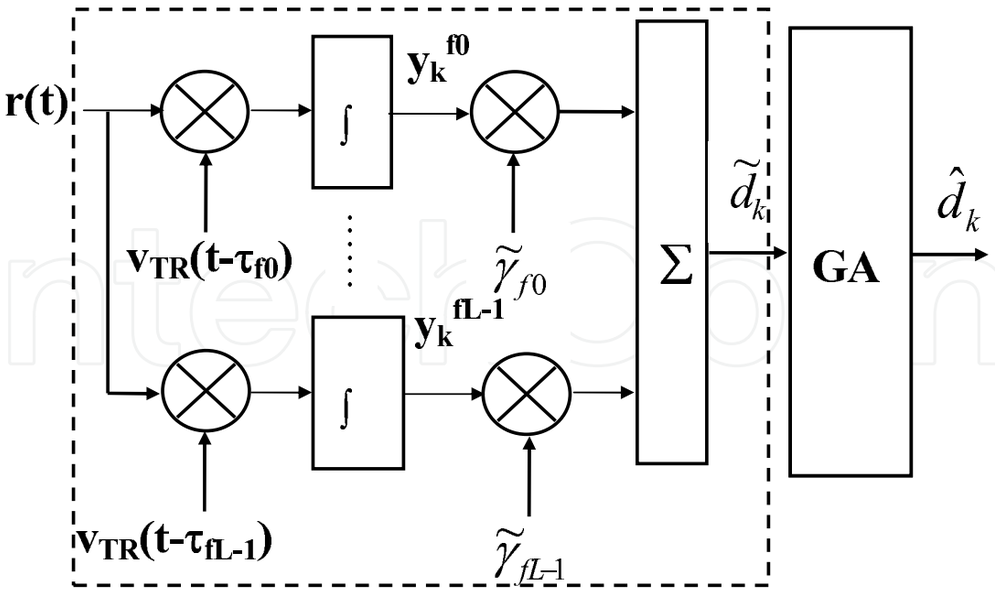


Fig. 1. RAKE-GA for DS-UWB system

3.1 Initialization of RAKE-GA

It is well known that a good initial value is critical in GA based algorithms. For DS-UWB systems, the performance of GA only receiver without proper initialization is even worse than RAKE receiver only due to the frequency selective nature of UWB channels. To this end we obtained our initial population for the GA optimization from the RAKE soft estimates so as to improve the BER performance of our system. A typical RAKE receiver is composed of several correlators followed by a linear combiner, as shown in Fig. 1. The signal received at the RAKE receiver is correlated with delayed versions of the reference pulse, which is the ternary orthogonal spreading sequence, multiplied by the tap weights, the output signals are then combined linearly Siriwongpairat & Liu (2008).

MRC-RAKE combiner, which uses the strongest estimated fingers to select the received signal at the delay times $\tau_{fl}\,(l = 0, ..., L-1)$**?**, was employed in this work. Perfect chip synchronization between the transmitter and the receiver is assumed. The l^{th} correlator's output y_k^{fl} of the RAKE receiver for the k^{th} desired symbol is given by

$$y_k^{fl} = \int_{kT_f+\tau_{fl}}^{(k+1)T_s+\tau_{fl}} r\,(t)\, v_{\mathrm{TR}}\left(t - kT_s - \tau_{fl}\right) dt. \tag{5}$$

Expression (5) in vector notation is expressed as shown in (6)

$$\mathbf{y_k} = \sqrt{E_s} d_k \mathbf{h} + \mathbf{i}_k + \mathbf{n}_k. \tag{6}$$

where $\mathbf{y}_k = \left[y_k^{f1}, ...y_k^{fL}\right]^T$, $\mathbf{h} = \left[h_{f1}, ...h_{fL}\right]^T$, $\mathbf{i}_k = \left[i_k^f, ...i_k^{fL}\right]^T$ with i_k^{fL} denoting ISI of the k^{th} symbol for the l^{th} correlator and $\mathbf{n}_k = \left[n_k^f, ...n_k^{fL}\right]^T$ with n_k^{fL} being the noise component of the k^{th} symbol for the l^{th} correlator. L is the number of RAKE fingers. $E_s = N_c E_c$ which is the energy per symbol. The Selective RAKE receiver output with MRC technique is expressed as

$$\tilde{d_k} = \tilde{\mathbf{fl}}^T \mathbf{y}_k. \tag{7}$$

where $\tilde{\mathbf{fl}} = [\tilde{\gamma}_1, ..., \tilde{\gamma}_L]^T$ is the finger weights of the RAKE receiver estimated from the channel taps, $\tilde{\gamma}_l = \hat{h}_{fl}$ where $\hat{h}_{fl}$=$\left[\hat{h}_{f1}, ...\hat{h}_{fL}\right]^T$ are the channel estimates. The results obtained in (7), which are soft estimates are used as initialization of GA optimization in the following section. The decision function is used to determine the estimated received data as follows:

$$\hat{d_k} = sign\left(\tilde{d_k}\right) \tag{8}$$

3.2 RAKE-GA

The Theory of GA

Despite the intuitive appeal and the symmetry of GAs, it is crucial that we back these fuzzy feelings and speculations about GAs using cold, mathematical facts. The schemata theory will help us to do this.The schemata theory and their net effect of reproduction and genetic operators on building blocks contained within the population for the GA are discussed below Goldberg (1989).

Schema Theory

The design methodology of the GA relies heavily on Holland's notion of schemata. It simply states that schemata are sets of strings that have one or more features in common. A schema is built by introducing a "don't care" symbol, "#," into the alphabet of genes, i.e., #1101#0. A schema represents all strings (a hyperplane or subset of the search space), which match it on

all positions other than "#." It is clear that every schema matches exactly 2' strings, where "r" is the number of don't care symbols, "#," in the schema template. For example, the set of the schema #1101#0 is $\{1110110, 1110100, 0110110, 0110100\}$ Tang et al. (1996).

Effect of Selection

Since a schema represents a set of strings, we can associate a fitness value $f(S,t)$ with schema "S, " and the average fitness of the schema. $f(S,t)$ is then determined by all the matched strings in the population. Using *proportional selection* in the reproduction phase as was done in our RAKE-GA algorithm, we can estimate the number of matched strings of a schema "S" in the next generation.

Let $\zeta(S,t)$be the number of strings matched by schema "S" at current generation. The probability of its selection (in a single string selection) is equal to $f(S,t)/F(t)$. where $F(t)$ is the average fitness of the current population. The expected number of occurrences of S in the next generation is

$$\zeta(S,t+1) = \zeta(S,t) \times \frac{f(S,t)}{F(t)} \tag{9}$$

Let

$$\varepsilon = (f(S,t) - F(t))/F(t) \tag{10}$$

If $\varepsilon > 0$, it means that the schema has an above-average fitness and vice versa.

Substituting (10) into (9) and it shows that an "above average" schema receives an exponentially increasing number of strings in the next generations as presented in (11)

$$\zeta(S,t) = \zeta(S,0)(1+\varepsilon)^t \tag{11}$$

Effect on Crossover

During the evolution of a GA, the genetic operations are disruptive to current schemata; therefore, their effects should be considered. Assuming that the length of the chromosome is P, which is the number of individuals within a population and scattered crossover is applied, in general, a crossover point is selected uniformly among $P-1$ possible positions.

This implies that the *probability of destruction* of a schema S is

$$p_d(S) = \frac{\sigma(S)}{P-1} \tag{12}$$

or the *probability of a schema survival* is

$$p_s(S) = 1 - \frac{\sigma(S)}{P-1} \tag{13}$$

where σ is the *defining length* of the schema S, defined as the distance between the outermost fixed positions. It defines the compactness of information contained in a schema. For example, the *defining length* of #OOO# is 2, while the defining length of 1#OO# is 3.

Assuming the operation rate of crossover is pc, the probability of a schema survival is:

$$p_s(S) \geq 1 - p_c.\frac{\sigma(S)}{P-1} \tag{14}$$

Effect of Mutation

If the bit mutation probability is p_m, then the probability of a single bit survival is $1-p_m$. Defining the *order* of schema S (denoted by $o(S)$) as the number of fixed positions (i.e.,

positions with 0 or 1) present in the schema, the probability of a schema S surviving a mutation (i.e., sequence of one-bit mutations) is

$$p_s(S) = (1 - p_m)^{o(S)} \tag{15}$$

Since $p_m \ll 1$, this probability can be approximated by:

$$p_s(S) \approx 1 - o(S).p_m \tag{16}$$

Schema Growth Equation
Combining the effect of selection, crossover, and mutation, we have a new form of the reproductive schema growth equation:

$$\zeta(S, t+1) \geq \zeta(S, t).\frac{f(S,t)}{F(t)}\left[1 - p_c.\frac{\sigma(S)}{P-1} - o(S).p_m\right] \tag{17}$$

Based on (17), it can be concluded that a high average fitness value alone is not sufficient for a high growth rate. Indeed, short, low-order, above-average schemata receive exponentially increasing trials in subsequent generations of a GA Tang et al. (1996).
Iterations of GA

- **Initialization of Population:** An initial random population was generated by using the soft estimates output of the RAKE receiver as the input to our GA. This was then converted to binary 0 and 1 from the soft estimates obtained from our RAKE receiver. The chromosomes fitness values are evaluated as discussed below.
- **Fitness Function Evaluation:** A fitness value is used to reflect the degree of *goodness* of the chromosome for the problem which would be highly related with its objective value Man et al. (1999). The fitness values of individuals within the population of our GA was evaluated before implementing the GA operations. The GA refine the specified population which consists of the chromosomes, through the selection, reproduction, crossover and mutation operations. The GA minimizes the fitness function in terms of the distance measure criteria. The probability density function of y_k in (6) conditioned on $\mathbf{h}$ *and* $\mathbf{d}$ is

$$p(\mathbf{y}|\,\mathrm{h}, \boldsymbol{d}) = \frac{1}{\left(2\pi\sigma_e^2\right)^{M/2}} \times \exp\left\{-\frac{1}{2\text{œ}_\mathrm{e}^2}\sum_{\mathrm{k}=1}^{\mathrm{M}}\left[\mathrm{y_k} - \sum_{\mathrm{l}=1}^{\mathrm{L_{tot}}}\mathrm{h_l d\,(k-l)}\right]^2\right\} \tag{18}$$

The joint ML estimate of $\mathbf{h}$ *and* $\mathbf{d}$ are obtained by maximizing $p(\mathbf{y}|\mathbf{h}, \mathbf{d})$ over $\mathbf{h}$ *and* $\mathbf{d}$ jointly. Equivalently, the ML solution is the minimum of the cost function **?** . The minimum of the cost function is evaluated to obtain estimate of the transmitted signal, $\hat{\mathbf{d}}$

$$J = \left|\tilde{\mathbf{fl}}^T\mathbf{e}\right| \tag{19}$$

where $\mathbf{e} = [\mathbf{e_1}, ..., \mathbf{e_M}]$, $\mathbf{e_k} = \left(\mathbf{y_k} - \sum_{\mathbf{l}=\mathbf{1}}^{\mathbf{L_{tot}}}\mathbf{h_l d\,(k-l)}\right)$and $k = 1 - M$
where all the terms are as defined in the section for initialization of RAKE-GA . An optimal solution is computationally expensive and so suboptimal solution like GA was adopted for estimating the data, $\hat{\mathbf{d}}$, while data-aided channel estimation approach was used in obtaining the channel estimates, $\hat{\mathbf{h}}$. The GA evaluated the fitness values of individuals by minimizing the cost function in (19).

- **Proportional fitness scaling** was used to convert the raw fitness score returned by the objective function to values in a range that is suitable for the selection function. It makes

the expectation proportional to the raw fitness scores. This is advantageous when the raw scores are in good range. When the objective values vary a little, all individuals have approximately the same chance of reproduction.

- **Stochastic selection** now chooses parents for the next generation based on their scaled values from the fitness scaling function. It lays out a line in which each parent corresponds to a section of the line of length proportional to its scaled value. There is a movement along the line in steps of equal size. At each step, a parent is allocated from the section it lands on. The first step is a uniform random number less than the step size. A certain **elites** are now chosen which are guaranteed to survive to the next generation.
- **Scattered crossover** combines two parents to form a child for the next generation. It creates a random binary vector, rv, then selects the genes where the vector is a 1 from the first parent, $P1$ and the genes where the vector is a 0 from the second parent, $P2$ and combines the genes to form the child. This is illustrated in (20)

$$\begin{aligned} P1 &= [1010010100] \\ P2 &= [0101101011] \\ bv &= [1100100101] \\ child &= [1001001110] \end{aligned} \tag{20}$$

- **Gaussian mutation** was used provides genetic diversity and enable the GA to search a broader space, by making small random changes in the individuals in the population. It adds a random number from a Gaussian distribution with mean zero to each vector entry of an individual. The variance of this distribution is determined by the parameters **scale** and **shrink**.

The scale parameter determines the variance at the first generation, that is, it controls the standard deviation of the mutation and it is given by $standard\,deviation = scale \times (v(2) - v(1))$, where $scale = 0 \sim 10$, v is the vector of initial range used to generate the initial population. The initial range is a 2-by-1 vector $v = 0; 1$.

The shrink parameter controls how the variance shrinks as generations go by. That is, it controls the rate at which the average amount of mutation decreases and the variance at the g^{th} generation G is given by $var_k = var_{k-1}\left(1 - shrink.\frac{k}{G}\right)$, where $shrink = -1 \sim 3$. If the **shrink** parameter is 0, the variance is constant, if the **shrink** is 1, the variance shrinks to 0 linearly as the last generation is reached and a negative value of **shrink** causes the variance to grow MATLAB (2007).

- **Stopping criteria** determines what causes the algorithm to terminate. Our algorithm was terminated when the refining of the chromosomes using the operators had been done G times, which is the number of generations.

The RAKE-GA receiver was proposed to reduce the high computational complexity of the RAKE-MLD receiver which is an optimum receiver in a frequency selective channel like UWB. In the MLD scheme, in which the whole search space of possible solutions are utilized, the soft estimate output, of the RAKE receiver is also used as the input to the MLD receiver. The MLD detector searches through all the possible solutions of data bits, $\left(M, 2^M\right)$ and the one close

in distance to the transmitted data based on the distance measure criteria is chosen. The cost function for the RAKE-MLD is also presented in expression (19) thereby making the MLD to spend longer simulation time and even to be more computationally complex.

4. Channel estimation

In this work, a data-aided approach used in Lottici et al. (2002) was also implemented in estimating the channel impulse response. The sliding window correlator method Li et al. (2003); Mielczarek et al. (2003) was used in estimating the channel gains and delays so as to reduce the high computational complexity of the ML approach. A data-aided approach for channel estimation is employed in this work and this implies that the transmitted signal, $x(t)$, is known to the receiver. The ML channel estimation has a very good performance but it is too complicated to be implemented in UWB systems which usually require low complexity receivers Siriwongpairat & Liu (2008). B known pilot symbols are sent for the training $d_k^t, (k = 1, 2..., B)$ in order to estimate the channel. The RAKE receiver gave an output during the training is presented as (21).

$$y_k^{L_{est}} = \int_{kT_f+\tau_{fl}}^{(k+1)T_f+\tau_{fl}} r^t(t)\, v_{\mathrm{TR}}\left(t - kT_f - \tau_{fl}\right) dt. \tag{21}$$

where $y_k^{L_{est}} = \left[y_k^1, y_k^2, ..., y_k^{L_{est}}\right]^T$, $r^t(t)$ is the received training signal for the k^{th} pilot symbol, L_{est} is the number of paths to be estimated and it is assumed that the receiver knows the optimal value of L_{est}(i.e.$L_{est} = L_{tot}$) in (3) Sato & Ohtsuki (2005). All other terms are as already defined in the previous Section.

The estimated path gains of the channel vector $\hat{\mathbf{h}} = \left[\hat{h}_1, \hat{h}_2, ..., \hat{h}_{L_{est}}\right]^T$, can be expressed as follows using the cross-correlation method, where E_s is the energy per symbol Sato & Ohtsuki (2005).

$$\hat{\mathbf{h}} = \frac{1}{B\sqrt{E_s}} \sum_{k=1}^{B} d_k^t y_k^{L_{est}}. \tag{22}$$

5. Computational complexity

We provide a complexity analysis of the proposed RAKE-GA in terms of complex valued floating point multiplication, in comparison with the RAKE, RAKE-MMSE and RAKE-MLD receivers. We assume all the receivers use the same channel estimation as presented in Section 4. Therefore, the complexity of channel estimation is not considered here. The order of complexity, $O(L_{est}M)$ is for the RAKE receiver. The RAKE-MMSE is of the order of $O\left(\left[L_c^3 + L_c^2 M + L_{est}M\right]\right)$. The RAKE-GA has an order of complexity $O\left(\left[GP\left(L_{est}M + logP\right)\right] + L_{est}M^2\right)$. The RAKE-MLD has a complexity of the order of $O\left(\left[M2^M\left(L_{est}M + log2\right)\right]\right)$. L_{est} is the number of paths to be estimated during the channel estimation process, M is the number of symbols per block, N_c is the length of the ternary orthogonal code sequence. G is the number of generations and P is the population size for the RAKE-GA. The computational complexities of the receivers depend on the derivation of the finger weights, the fitness function evaluation and the demodulation of the signal.
Table 1 shows the complexities of the RAKE, RAKE-MMSE, RAKE-GA and RAKE-MLD at $L_{est} = 1024$. The RAKE-MMSE, RAKE-GA and RAKE-MLD were normalized to the RAKE receiver being the least complex receiver but with poor BER performance. The

RAKE-MMSE is five times more complex than the RAKE receiver but has corresponding improved performance. The RAKE-GA is more complex than the other two receivers but obviously with much better BER performance with no error floor as encountered in the other receivers. The RAKE-MLD is the most complex of the four receivers but with the best BER performance. The BER of the RAKE-GA is very close to the RAKE-MLD with a huge reduction in the complexity of the RAKE-GA when compared to the RAKE-MLD.

Receiver	Parameters	Normalized
RAKE Sato & Ohtsuki (2005)	M=100	1
RAKE-MMSE Eslami & Dong (2005)	M=100,Lc=5	5
RAKE-GA	M=10,P=100,G=10	103
RAKE-MLD	M=10	1025

Table 1. Computational Complexity ($L_{est} = 1024$)

6. Simulation results

6.1 Simulation setup

The simulation for the RAKE Sato & Ohtsuki (2005), RAKE-MMSE Eslami & Dong (2005), RAKE-GA and RAKE-MLD receivers were carried out using BPSK modulation at a transmission rate of $R_b = 250$Mbps with symbol duration or frame length of $T_f = 4$ns. Each packet consists of 1000 symbols. A ternary code length of $N_c = 24$ was used for spreading, with a chip width of $T_c = 0.167$ns. The simulated IEEE 802.15.3a UWB multipath channel model with data-aided channel estimation using pilot symbols of $B = 10 \sim 100$ for a single user scenario was employed for the simulation. The channel model 3 (CM3) Foerster (2003) which is a non-line-of-sight (NLOS) environment with a distance of $4 \sim 10$m, mean excess delay of 14.18ns and RMS delay spread of 14.28ns was considered in this work. The number of RAKE fingers used are $L = 5, 10, 15, 20$. The equalizer taps of $L_c = 5$ was used for the RAKE-MMSE.

For the proposed RAKE-GA approach, the population size was $P = 50$ and 100 while the number of generations was $G = 1 \sim 20$. The proportional scaling was employed for the scaling of the fitness values before selection. The crossover of 0.85 was used with an elite count of 0.05. The Gaussian mutation values are $shrink = 1.0$ and $scale = 0.75$. In addition, the unconstrained minimization hybrid function was employed to improve the fitness values of the individuals within the population.

6.2 Performance evaluation

Fig. 2 shows the BER performance of RAKE, RAKE-MMSE, RAKE-GA and RAKE-MLD receivers at $L = 10$ for both known CSI and pilot-aided channel estimation scenarios. The four receivers performed better as expected when the CSI is provided as the channel estimation errors incurred will degrade the performances. The error floors encountered by both the RAKE and RAKE-MMSE receivers were taken care of by the RAKE-GA and RAKE-MLD as explained thus:

- The **RAKE** receiver cannot capture a large signal energy with few number of RAKE fingers and more so a RAKE with MRC weight estimation cannot remove ISI. RAKE receiver also needs very high number of pilot symbols during the channel estimation as the channel estimation error incurred using a few number of pilot symbols resulted in the performance being degraded.

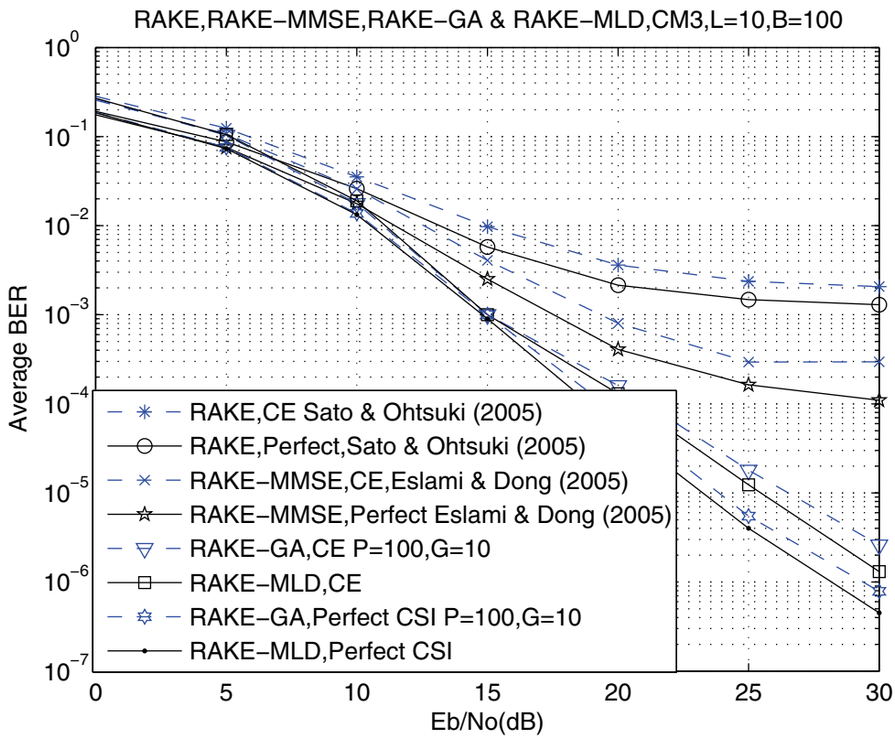


Fig. 2. BER vs. SNR for all receivers

- The **RAKE-MMSE** receiver achieves better BER than RAKE receiver because the equalizer removes the ISI symbol by symbol but the error floor is still encountered since the RAKE receiver output with few RAKE fingers is the input to the equalizer so the RAKE-MMSE cannot capture a large signal energy.
- The **RAKE-GA** receiver on the order hand has no error floor with the same number of RAKE fingers as the other two receivers because it is able to remove the ISI using the distance measure criteria. The soft estimates of the RAKE receiver was a very good initial population choice for the GA and so was the reason for the improvement in performance. The RAKE-GA performs well even with moderate number of pilot symbols.
- The **RAKE-MLD** receiver had the best BER performance as is the optimal receiver which is able to remove the ISI and capture a large signal energy using a few RAKE fingers and not very high pilot symbols since the RAKE receiver output was also the input into the RAKE-MLD receiver.

Fig. 3 shows the BER against SNR for the RAKE-GA receiver at $P = 100$, $G = 10$ at values of $L = 5, 10, 15, 20$. This shows the impact of the number of RAKE fingers on the performance of the scheme. This BER performance improvement is as a result of increase in the number of RAKE fingers. The RAKE-GA at $L = 5$ was of higher BER to the system when $L = 10, 15, 20$ where they were almost of the same BER at all SNR values.
Fig. 4 shows the impact of the number of generations in the BER performance, where $G = 1 \sim 20$ for $P = 100$ and $G = 2 \sim 20$ for $P = 50$ both at $L = 10$ to show the speed of convergence of the algorithm assuming a known CSI. The algorithm at $G = 1 \sim 10$ for $P = 100$ gave better BER generally than at $G = 2 \sim 20$ for $P = 50$. It can thus be concluded that the GA with a

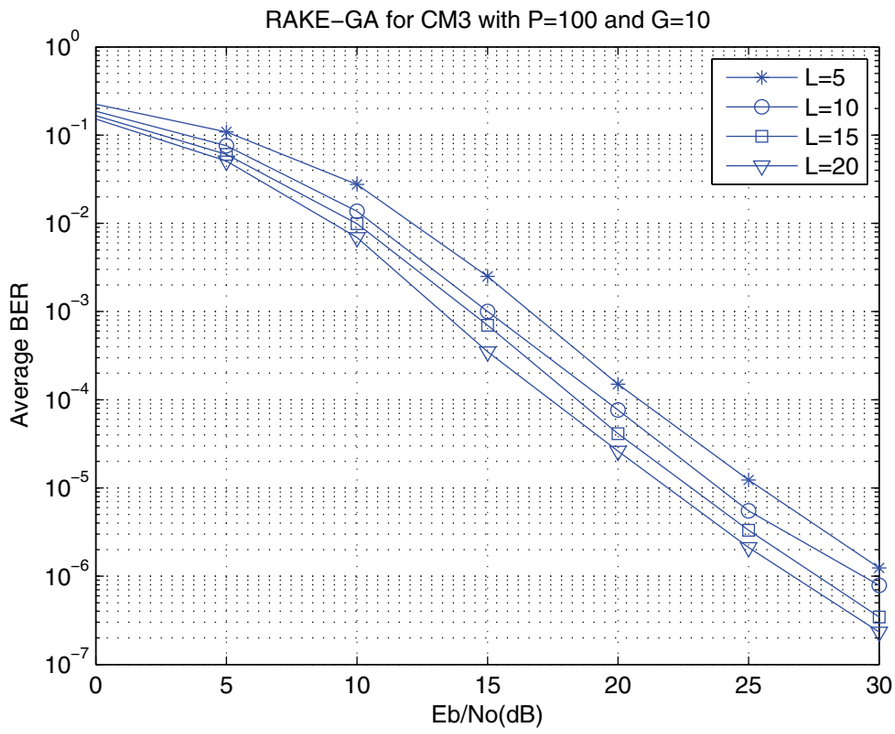


Fig. 3. BER vs. SNR for RAKE-GA

relatively large population size achieves a lower steady state BER than the case with only half the population size at a cost of slightly more generations.
Fig. 5 shows how the BER of the RAKE-GA receiver with channel estimation decreases with increase in the number of pilot symbols giving us the number of training overhead for the pilot-aided channel estimation.

7. Conclusion

We have proposed a GA based channel equalization scheme in DS-UWB wireless communication and compared the results obtained from intensive simulation work with the RAKE, RAKE-MMSE and RAKE-MLD for both known CSI and pilot-aided channel estimation scenarios. Our simulation results show that the proposed RAKE-GA receiver significantly outperforms the RAKE and the RAKE-MMSE receivers. The GA based scheme also gives a very close BER performance to the optimal MLD approach at a much lower computational complexity. Moreover, we have investigated the effect of the number of RAKE fingers, the population size and the pilot overhead on the BER performance. RAKE-GA obtains a good performance with a moderate number of RAKE fingers and a further increase in the number of RAKE fingers has little effect on the performance. GA with a relatively large population size achieves a lower steady state BER than the case with only half the population size at the cost of slightly more generations. And the pilot overhead of 10% is enough for training to obtain comparable performance with the case of perfect CSI.

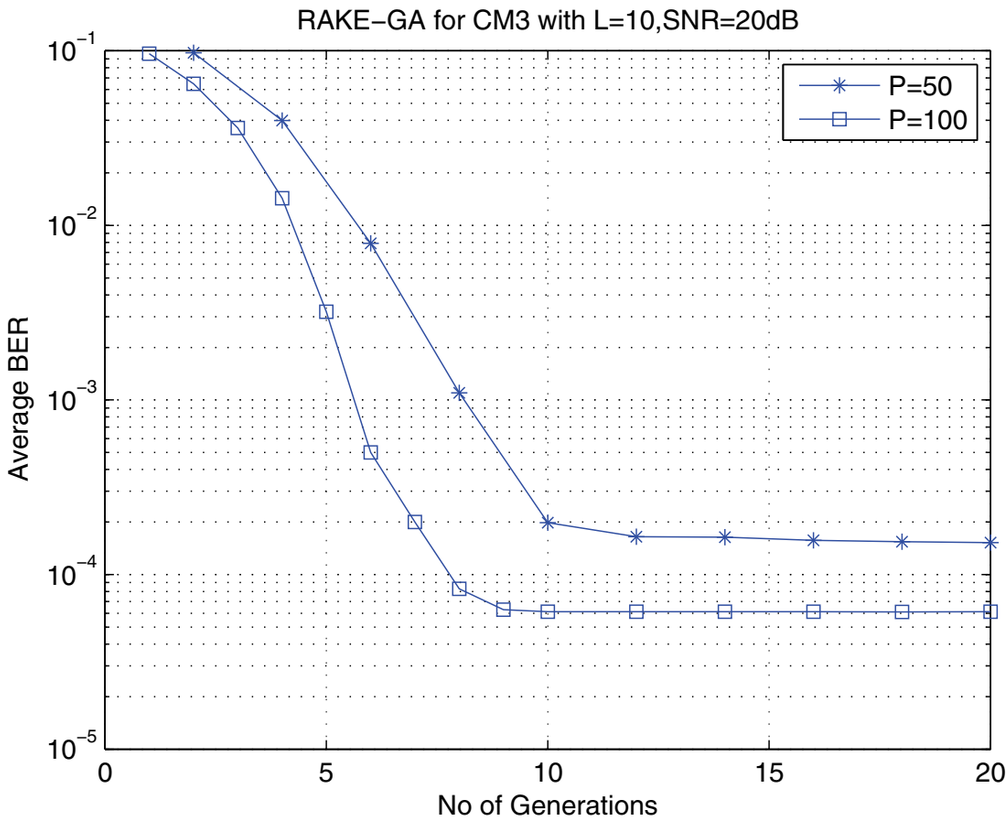


Fig. 4. Convergence speed of RAKE-GA

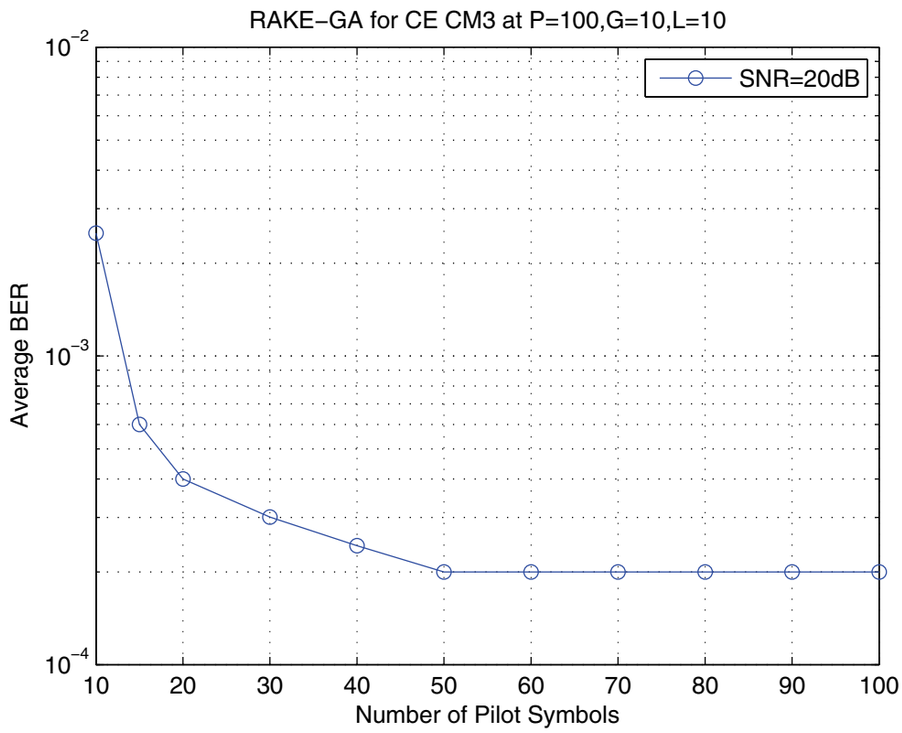


Fig. 5. Impact of Pilot size on RAKE-GA

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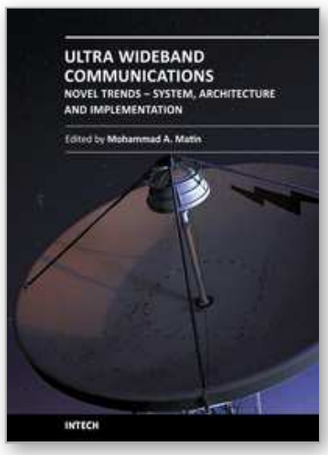
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