Equalization of DS-UWB Systems using Genetic Algorithm with Adaptive Parameters

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***Abstract*—** We use adaptive generation along with some other parameters to investigate their effects on the performance of Genetic Algorithm (GA) in comparison to a previous work, where the output of a RAKE receiver is utilized as the input to a GA so as to reduce the inter-symbol interference (ISI) due to the frequency selectivity of UWB channels because of the very high rate of transmission. The effects of two different scaling methods and two mutation types, on the performance of a GA when used with a receiver for the equalization of the channel of a direct sequence ultra wideband (DS-UWB) wireless communications system are presented. The results show that fitness scaling has effects on GA based optimization while mutation prevents local convergence.

***Keywords*—**Genetic algorithm, stall generation, function tolerance, fitness limit, adaptive parameters.

1. **Introduction**

Ultra wideband (UWB) communication has been defined as one of the most promising technologies, where the very large bandwidth of 3.1−10.6 GHz allows UWB to be applicable for communication systems that are innovative and at the same time transmitting at a very fast rate and an efficient manner (Perarasi & Ravichandran, 2014). In (Somayazulu et al., 2002), the data rate and the coverage distance of UWB as a promising technology was given as 110 Mbps to 480 Mbps at distance of 2 m to 10 m respectively. The low power spectral density of UWB and its benefits was also explained by (Nassar et al, 2003.).

The application of RAKE receivers to UWB was done earlier in 2005 by (Sato & Ohtsuki, 2005), where it was shown that when maximum ratio combining when used with RAKE receiver has low computational complexity even though it was a perfect channel estimation that was considered. In another related research work by (Siriwongpairat & Liu, 2008), narrowband interference (NBI), ISI and multipath fading are challenges for a channel that the fading is frequency-selective and so all these severely degrade the performance of the UWB system considered. It was concluded in the work that multipath diversity can be exploited by the constructive combination the monocycles that was obtained from the paths that are resolvable.

In previous work by these authors (Surajudeen-Bakinde et al, 2009), the lower computational complexity of genetic algorithm as optimization technique used for UWB, was shown to be much lower than maximum likelihood detection approach.

II. Related Work

Optimization techniques as applied to UWB was taken to different level by (Montaser et al., 2013), where Modified Particle Swarm Optimization (MPSO) and Bacterial Swarm Optimization (BSO) in addition to Central Force Optimization (CFO) was as recent optimization technique to optimize a notched-UWB E-shaped patch antenna. The return loss, antenna gain and radiation patterns which are the antenna parameters were also discussed.

For the enhancement of a multi-objective genetic algorithm, a machine learning technique was applied by (Martins et al, 2012), whereby a microstrip antenna used in ultra-wideband (UWB) wireless devices, was analyzed so as to know the estimates of the fitness function behaviours, from a set of experiments made in a laboratory. A novel genetic algorithm (GA) that is based on complementary error function mutation (CEFM), was used as a differential multiuser detection (MUD) method for ultra-wideband (UWB) systems by (Qi et al., 2011). In another research, a multiuser detection (MUD) method using a novel genetic algorithm (GA) based on complementary error function mutation (CEFM) and a differential algorithm (DA) for ultra-wideband (UWB) systems was proposed by (Kong et al, 2011). Six existing forms of fitness scaling in genetic algorithms were presented, as the first systematic means of evaluating the effects of the fitness scaling functions was compared to a new method that is called transform ranking. The number of generations used was fixed for the stochastic universal sampling which was applied individually. (Hopgood & Mierzejewska, 2009).

The statistical analysis of the minimum mean square error (MMSE) was done for the investigation of the problem encountered in the finger selection process for a UWB Selective Rake receiver. An iterative scheme based on GA was proposed because the optimal solution is NP hard (Gezici et al., 2005). B-spline basis approximation was used as a flexible method of designing UWB pulse waveform by some researchers, (Wang et al., 2008). The power spectral mask of the Federal Communications Commission (FCC) for indoor UWB systems must be met in addition to ensuring that in the design of UWB, the orthogonality is also preserved at the correlation receiver (Wang et al. 2008).

Hill and the other researchers in (Hill et al., 2004), made a comparison between the effectiveness of using fitness scaling in a GA and using an inversion operator in a GA. In (Sadjadi, 2004), four scaling methods were compared based on their handling of a simple set of optical processing data. Also in (Kreinovich et al., 1993), problem of choosing a scaling function as a mathematical optimization was formulated.

In all the above researches in GA as optimization techniques and its application to UWB, no work has been done in investigating the performance of applying adaptive parameters to channel equalization of DS-UWB communication systems using GA. In this work, we use adaptive parameters to know their effects on the performance of GA as an optimization technique in comparison to a previous work (Surajudeen-Bakinde et al., 2009). A plot of the bit-error-rate (BER) versus the size of the generation used is obtained to show the rate at optimization is converging. The effects of two different scaling methods and mutation types on the performance of the channel equalization of the DS-UWB systems using a GA as an optimization technique was also investigated. This work is an extention of work done in (Surajudeen-Bakinde et al., 2009).

This paper is organized such that we reviewed work done in the same field of research in Section II. Section III is the system model. The equalization of DS-UWB system using GA is given in Section IV. The results obtained from the simulation is given is in Section V and finally, the paper is concluded in Section VI.

III. System Model

A. Signal Transmitted

The ternary orthogonal code sequence which is the transmit pulse vTR (t), is generated in accordance to the expression given thus:

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

where the length of the spreading code is N_c, *the* i_{th} component of the spreading code is b_i, the chip width is T_c and represents the transmitted monocycle waveform that is already normalized to have unit energy is $g(t)$

The expression that follows is for the DS-UWB signal:

$$x(t) = \sqrt{E_c} \sum_{k=-\infty}^{\infty} d_k v_{TR}(t - kT_f) \qquad (2)$$

where the energy for each transmitted pulse is E_c , the $d_k \in \{\pm 1\}$ is the k_{th} transmit symbol, T_f is the frame time and each of the frame considered is further divided into N_c

which are equally spaced chips that give rise to $T_f = N_c T_c$.

B. Channel

According to (Foerster, 2003), the UWB channel model which was derived from the Saleh-Valenzuela model and has undergone some modifications is employed the simulation done in this work. Instead of using a Rayleigh distribution, the model used a log-normal distribution for the multipath gain magnitude and this was because it is found to have a better fit the measurement data. Also, an assumption of independent fading is taken for the individual cluster and equally for each ray within the cluster. In a simpler form, the channel impulse response of the Saleh-Valenzuela model is given thus:

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

where the total number of paths for this work is L_{tot}, with a delay τ_l (= lT_c) for the l_{th} component, where the l_{th} path gain is h_l (Foerster, 2003).

C. Signal Received

The signal received as a result of the convolution of the signal transmitted which is given in (2), with the defined channel impulse responses in discrete time, given in (3) and then the addition of the noise component, which is the additive white Gaussian noise (AWGN), is given in the equation that follows thus:

$$r(t) = x(t) * h(t) + n(t)$$

$$= \sqrt{E_c} \sum_{k=-\infty}^{\infty} d_k v_{TR} \sum_{l=1}^{L_{tot}} h_l \left(t - kT_f - \tau_l\right) + n(t)$$

(4)

where $n(t)$ is the AWGN, having a variance of σ^2 and zero mean.

IV. Channel Equalization of DS - UWB Communication System Using GA

A. RAKE Receiver

The importance of a good initial value in GA based algorithms was put into consideration in this work. When GA only, without proper initialization was applied to DS-UWB systems, the performance is worse than RAKE receiver only. This is because of the frequency selective nature of UWB channels. For this reason, the RAKE output soft estimates was used as the initial population for the channel equalization so as to have an improved performance of our system.

(Siriwongpairat & Liu, 2008) defined a typical RAKE receiver as one that has many correlators which is then followed by a linear combiner. An assumption of having a channel without requiring estimation at perfect chip synchronization is also assumed to be between the transmitter and the receiver. The output of the correlator which is expressed in vector is expressed in the next expression.

$$y_k = \sqrt{E_s} d_k h + i_k + n_k \qquad (5)$$

where $y_k = \left[y_k^{f1}, \ldots y_k^{fL}\right]^T$, $E_s = N_c E_c$, which is the energy per symbol,

$h = \left[h_{f1},...h_{fL}\right]^T, i_k = \left[i_k^{f1},...i_k^{fL}\right]^T$ with i_k^{fL} denoting ISI of the k_{th} symbol for the l_{th} correlator and $n_k = \left[n_k^{f1},...n_k^{fL}\right]^T$ with n_k^{fL} is the noise component of the k_{th} symbol for the correlator l_{th}. The number of RAKE fingers used is symbolized with L

B. Genetic Algorithm

According to (Man et al., 1999), the definition of GA was given as a technique that works on the Darwinian principle of natural selection which is referred to as "survival of the fittest". The researchers went on to explain that the degree of goodness of the chromosome being considered for the problem, which in any case would be highly related with its objective value is shown by the fitness value. A better solution is more likely to emerge from a fitter chromosome, which invariably yield good quality offspring, throughout a genetic evolution. The number of possible solutions, searched during the optimization process using the GA, are specified, before refining is done using the GA operators. Minimization of the fitness function is done by the GA in terms of the distance measure criteria according to the cost function given thus:

$$J = \left|\gamma^T e\right| \quad J = \left|\gamma^T e\right| \qquad (6)$$

where

$e = \left[e_1...,e_M\right], e_k = y_k - \sum_{l=1}^{L_{tot}} h_1 d(k-1)$ and $k = 1 - M$. $\gamma = \left[\gamma_1,...\gamma_L\right]^T$ is the weights of the finger for the RAKE receiver which is being estimated from the channel taps that is given as, $\gamma_l = \lfloor h_{fl} \rfloor$. The other terms have already being defined in the RAKE-GA initialization section.

V. Fitness Scaling and Adaptive Parameters for GA Based Equalization

A. Types of Fitness Scaling

Fitness scaling converts the raw fitness scores that are
returned by the fitness function to values in a range that is suitable for the selection function. The selection function assigns a higher probability of selection to individuals with higher scaled values. The range of the scaled values affects the performance of the GA. Two scaling options compared in this paper are rank and proportional methods.

• Expectation is proportional to the scores of the raw fitness in a GA when **proportional fitness scaling is implemented**. The advantage to this is beneficial when you have good range for raw scores. When the scaled values do not vary too much as the individuals with the highest scaled values reproduce too rapidly, a good and suitable range is thus obtained so as to avoid it taking over the population gene pool to quickly, and preventing the genetic algorithm from searching other areas of the solution space. Also the range should vary a widely so as let the individuals have almost the same chance of reproduction and the search will equally progress quite slowly (MATLAB, 2007).

• The raw score using the **rank fitness scaling**, is scaled when it is based on the rank of each member and not the score. The position in the sorted scores is rank of an individual and the fittest individual is ranked 1, the fitter individual is has a rank of 2, and so on. A scaled value is assigned such that, the scaled value of an individual with rank n is proportional to $\frac{1}{\sqrt{n}}$. The effect of the spread of the raw scores is thus removed (MATLAB, 2007).

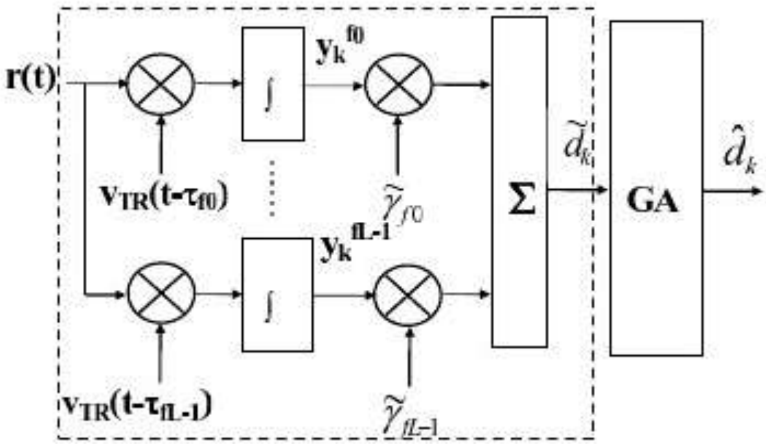

Figure 1. Block Diagram of RAKE-GA for DS-UWB

B. Operators in RAKE-GA for DS-UWB System

The block diagram of the RAKE receiver, as being the input to the RAKE in combination with the GA for the DS-UWB system is presented in Fig. 1. The three main GA operators implemented in this work are as described thus:

• **Stochastic selection** is the method used to choose parents, based on their scaled values from the fitness scaling function, for the next generation. A line is now laid out, whereby each parent correspond to a section of the line of length proportional to its expectation. Elites that are guaranteed to survive to the next generation are then chosen.

• Two parents come together to produce a child for the next generation when **scattered crossover** is implemented in a GA operation. The genes are selected by the created binary vector, whereby the genes where the vector is a 1 comes from the first parent, and the genes where the vector is a 0 comes from the second parent. The combination subsequently takes place for a child to be formed.

• **Gaussian mutation and uniform mutation** are two different mutation types employed in this work. Convergence to a local minimum point is prevented by the mutation types. A random number, which has a mean of zero is added from a

Gaussian distribution to each of the vector entry of an individual. The scale and shrink parameters are used to control the variance of the distribution. The variance at the first generation is determined by the scale parameter, while shrinking of the variance as generations go is controlled by the shrink parameter. Uniform mutation on the other hand is a two-step process, firstly the algorithm selects a fraction of the vector entries of an individual for mutation, where each entry has the same probability as the mutation rate of being mutated. Secondly, the algorithm replaces each selected entry by a random number selected uniformly from the range for that entry (MATLAB, 2007).

C. Adaptive Parameters in RAKE-GA for DS-UWB

The algorithm is terminated by setting the **stopping criteria** to terminate. The maximum generations for the algorithm, which was fixed in our previous work (Surajudeen-Bakinde et al., 2009) is termed the **Generations.** Three more stopping criteria, namely, fitness limit, stall generations and function tolerance are implemented in this work. The algorithm is stopped, by the fitness limit. This occurs for the best point in the current population, when the value of the fitness function is less than or equal to the specified fitness limit value. When the weighted average change in the fitness function value, over the specified stall generations is less than the specified function tolerance, then the algorithm is stopped by the Stall generations. The algorithm runs until the function tolerance stops it when the weighted average change in the fitness function value over the specified stall generations is less than the specified function tolerance.

VI. Simulation Results

A. Simulation Setup

The modulation type implemented in this simulation work is the Binary Phase Shift Keying which was at a transmission rate of Mbps at a frame length of ns for the RAKE-GA receiver. There are 1000 symbols in each packet. Spreading is carried out using a ternary code whose length is 24 and at a chip width of 0.167 ns. The UWB multipath channel model as specified in (Foerster, 2003) which does not need channel estimation, considering a single user is used in this simulation. The channel model 3 (CM3), which is a non-line-of-sight (NLOS) environment, at a distance of 4 ~ 10 m, having an average excess delay of 14.18 ns and RMS delay spread of 14.28 ns is the one implemented. L = 10 RAKE fingers is used in the simulation setup.

The population sizes used are P = 20, 40, 50, 60, 80, and 100 with a maximum number of generations being specified as G = 50, 25, 20, 17, 13, and 10 are implemented for the RAKE-GA approach in this work. The fitness limit values are Fl = 0.3, 0.25, 0.2, 0.15, 0.1 and 0.05 and the function tolerance used are Ft = 1e − 6, 1e − 7, 1e − 6, 1e − 8, 1e − 9, and 1e – 10 while the stall generations are StG = 25, 12, 10, 8, 6, and 5. Elite count of 0.05 and crossover of 0.85 was used in this set-up. A value of shrink = 1.0 and scale = 0.75 for the Gaussian mutation and 0.01 is the uniform mutation rate used.

B. Performance Evaluation

The BER performance of the algorithm is presented in Fig. 2 at P = 50 and 100 and maximum generation of G = 20 and 10 for proportional + Gaussian and rank + uniform scenarios with adaptive and fixed parameters respectively. The curve with adaptive and fixed parameters were of the same BER at SNR of 0 − 15dB, despite the fact that population size for adaptive was half of the one used for fixed. Fig. 3 is to compare the performance of rank + uniform, proportional + Gaussian, rank + Gaussian and proportional + uniform, using the same simulation parameters as listed in the previous section. In the figure, rank + uniform and rank + Gaussian are almost of the same BER as the small difference at some population sizes are insignificant. The same applies to proportional + Gaussian and proportional + uniform as we have almost same BER values with insignificant differences at few points. In Fig. 4, we showed the effects of using adaptive parameters on the BER performance of the RAKE-GA for all the four combinations of the two scaling and mutation methods. Fig. 5 shows the population sizes against the two different generations used in the simulation and one obtained after the simulation. We are able to show, that the optimization was terminated in all the cases, with the scenario where Gaussian mutation using more generations than when uniform mutation. All the four scenarios have the same maximum and stall generations as they were specified.

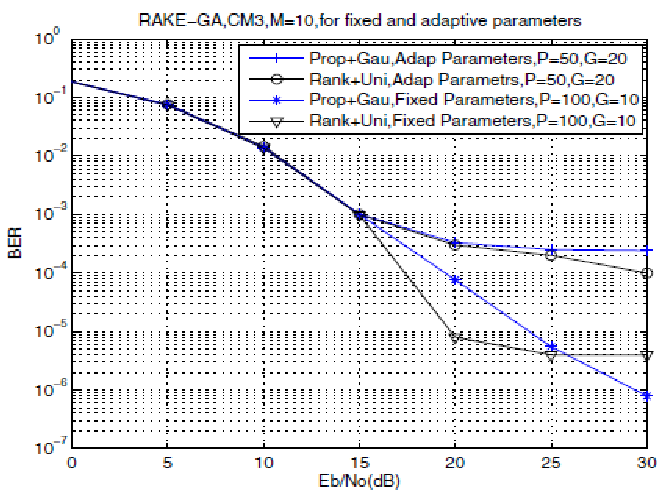

Figure 2: Performance of RAKE-GA IN CM3

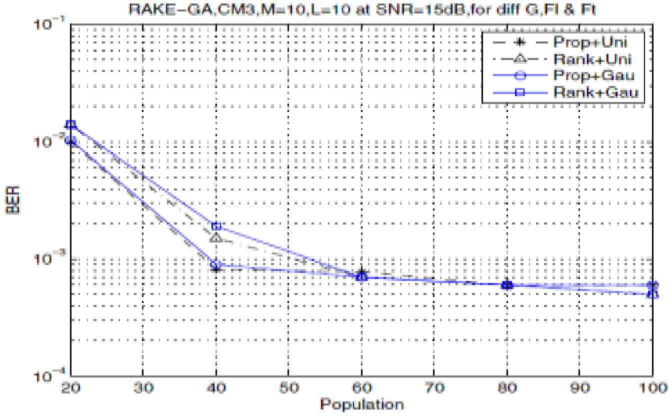

Figure 3: Effect of Population size on Performance of RAKE-GA for CM3

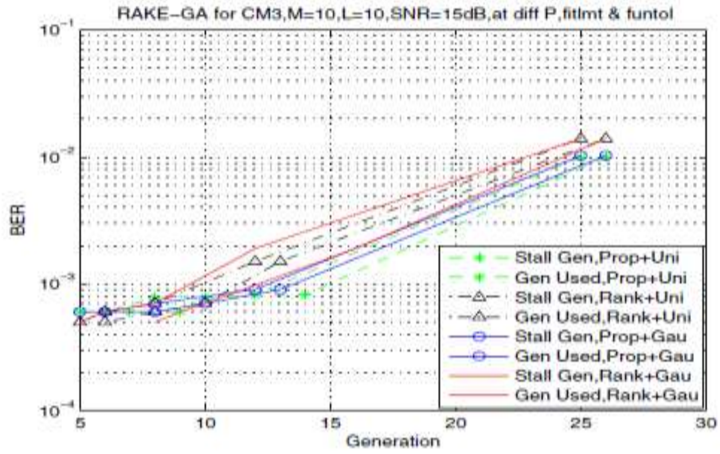

Figure 4: BER vs. Generation for CM3 for RAKE-GA

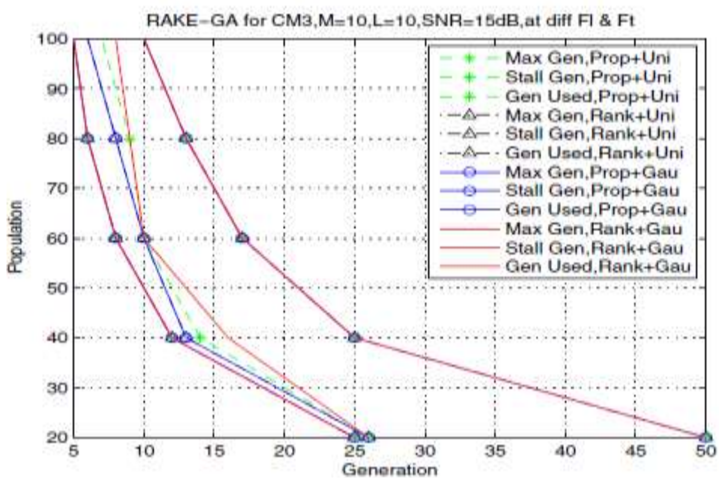

Figure 5: Population size vs. Generation Size for CM3 for RAKE-GA

VII. Conclusion

This research work has been able to conclude that fitness scaling plays very important role in the GA optimization. The mutation on the other hand, has no effect but prevents local convergence. Properly chosen adaptive parameters also improve the performance of the GA. We are able to reach this conclusion from the results of our investigation into the effect of scaling methods and mutation types on the performance of the equalization of the channel for the DS-UWB system using GA as an optimization technique in combination with a RAKE receiver. Two different types of scaling and mutation functions were considered.

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