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Genetic Algorithm Assisted Channel Estimation for Multi-user Communication Systems

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Abstract: - A novel multiuser code division multiple access (CDMA) channel estimator based on genetic algorithm is considered which estimates the fading channel impulse response coefficients of all the users. Furthermore, the optimum multiuser detector, based on the maximum likelihood (ML) rule, is developed in order to identify the transmitted data sequence. As is demonstrated in simulation results, the proposed method in channel estimation is much more accurate. As a result, we can achieve a near-optimum bit error rate (BER) performance upon perfect channel estimation.

Key-Words: - Channel estimation, Genetic algorithms, CDMA and Multi-user communications.

1 Introduction

Code division multiple access (CDMA) [1]-[2] constitutes an attractive multiuser scheme that allows users to transmit at the same carrier frequency in an uncoordinated manner. However, this creates multiple access interference (MAI), which-if not controlled-can seriously deteriorate the quality of reception. Numerous methods have been proposed for reducing the amount of MAI present in the received signal, such as power control, the optimization of signature sequences, and sectorized antennas. Nevertheless, these techniques have their limitations in combating the effects of MAI, in conjunction with the conventional multiuser detector, since the MAI is treated as noise. The optimum multiuser detector [3] based on the ML rule has a computational complexity that is exponentially increasing with the number of users. Hence, the optimum ML multiuser detector is impractical to implement. This complexity constraint led to numerous suboptimal multiuser detection proposals which sacrifice performance for the sake of a reduced complexity. In particular, the reduced complexity tree-search type algorithms [4]-[5] based on the ML rule with a specific number of surviving paths were shown to achieve a near optimum performance, when used in conjunction with a noise whitening filter. However, some form of memory is required at the receiver in order to store the metrics of the surviving paths. Conventionally, the fading channel impulse response (CIR) coefficients are usually estimated using a pilot signal [6] as, for example, on the downlink of the IS-95 system [7] in order to facilitate coherent detection. However, this technique becomes inefficient on the uplink, since an independent pilot signal is required from each user in order to estimate the independent fading CIR coefficients experienced by each user's signal. Consequently, to achieve a optimum BER, a perfect channel estimation method should be exerted. The results obtained clearly demonstrate that the GA-based scheme has superior performance.

2 System Description

We consider a symbol-synchronous CDMA system, where K users transmit data packets over a single-path frequency-nonselective slowly Rayleigh fading channel, and hence, no multipath diversity can be exploited. Assuming ideal low-pass filtering, the baseband received signal [8] is given by

$$r(t) = S(t,b) + n(t) \tag{1}$$

Where $n(t)$ is the zero-mean complex additive white Gaussian noise (AWGN) with independent real and imaginary components, each having a double-sided power spectral density of $N_0/2$ and

$$S(t,b) = \sum_{i=0}^{M-1}\sum_{k=1}^{K} \sqrt{\varepsilon_k}\, C_k^{(i)}\, b_k^{(i)}\, a_k(t - i\,T_b) \tag{2}$$

In (2), M is the number of data bits in a frame transmitted by each user, ε_k is the bit energy of the k-th user, T_b is the signalling interval, T_b is the frame duration, and $a_k(t)$ is the signature sequence of the k-th user associated with a processing gain of N_c. However, our proposed detector is capable of handling sequences of long period, as long as the cross-correlations between the users' signature sequences over each signalling interval are known to the detector. The unknown variables in (2) are

$b_k \in \{+1,-1\}$ and $C_k^{(i)}$, which denote the i-th bit and the corresponding complex CIR coefficient of the k-th user, respectively. The channel is assumed to be slowly fading, such that $C_k^{(i)}$ may be taken to be constant over one signalling interval and the fading is independent for all users. It is also assumed that $C_k^{(i)}$ varies over the duration T_b of the M-bit transmission frame according to the Doppler frequency f_d. At the receiver, a bank of filters matched to the corresponding set of the users' signature sequences is sampled at the end of the i-th bit interval. In this paper, we are interested in determining the CIR coefficients $C_k^{(i)}$ for $k = 1, \ldots, K$ and $i = 0, \ldots, M-1$ at the receiver, in order to perform coherent detection of the received signals.

3 Genetic Algorithm Based Channel Estimation

The efficiency of any global positioning technique can be measured in terms of two properties the explorative property and the exploitative property [9]. Techniques that possess a high explorative property have a slower convergence rate and a higher computation complexity but they explore the entire space in order to locate the global optimum. Hence, accuracy is always guaranteed. Techniques such as the family of hill-climbing methods possess a high exploitative property, and hence they offer fast convergence to an optimum of a given subspace. However, this optimum may not be the global optimum of the entire solution space.

GAs [10]-[11] constitute robust global search and optimization strategies that can strike an attractive balance between exploitation and exploration. These algorithms were introduced by Holland [11], and their principles are based on the concept of natural evolution. Specially, GAs use a population of candidate solutions initially distributed randomly over the entire solution space. Hence, GAs are highly explorative at the beginning. By evolving this population of candidate solution over successive iterations or generations, through probabilistic transition operations based on Darwinian survival of the fittest, the GA quickly identifies and exploits the subspaces, in which the global optimum may be located, while at the same time maintains the exploration of other parts of the solution space. Hence, while the optimum solution is not always located, the GA has a low probability of curtailing the exploration in suboptimal, rather than optimal solutions. The first step in applying GAs is to encode the parameters to be optimized. We use the popular value encoding scheme. A simple GA usually consists of three operations, namely, selection, crossover, and mutation, at each cycle. Elitism and migration strategies which automatically copy a few of the best solutions in the population into the next generation are often incorporated.

3.1 Initialization

Initialization of the GA is performed at the so-called ($g = 1$)st generation for each new signaling interval, as seen in Fig. 1, by creating p number of candidate solutions, or strings in GA parlance. The set of p strings is known as a population, and p is known as the population size. These strings represent the unknown variables of interest, which in this case are the coefficients of the channel $C_k^{(i)}$. Hence, each string will contain elements corresponding to the K users, each assuming a certain value.

As seen in Fig. 1, the parameter t is associated with the GA generation corresponding to the termination of the search.

3.2 Evaluation

Associated with the p-th combination string is a so-called figure of merit-more commonly known in GAs as the *fitness* value-which has to be evaluated, as seen in Fig.1. The fitness value is denoted by $f\left[\tilde{C}_p^{(i)}\right]$ for $p = 1, \ldots, P$. Then we exert GA operations such as selection, crossover, mutation and migration on our population in order to reach the best fitness threshold (T).

3.3 Selection

The exploitative property of GA is derived from two GA operations referred to as selection and crossover. The crossover operation will be explained in the next subsection. Let us refer to the elements that constitute the optimal solution as good elements. Any other elements are referred to as bad elements. For example, if the optimal solution constitutes a string containing all $+1$ elements, then any $+1$ in a string will be a good element while any -1 in the string will be a bad element. Intuitively, strings having a high fitness will contain more good elements and hence should be exploited further. At

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the same time, strings having a low fitness value should be discarded.
Two commonly used methods of selection we use in our simulations are Stochunif and Roulette selections.

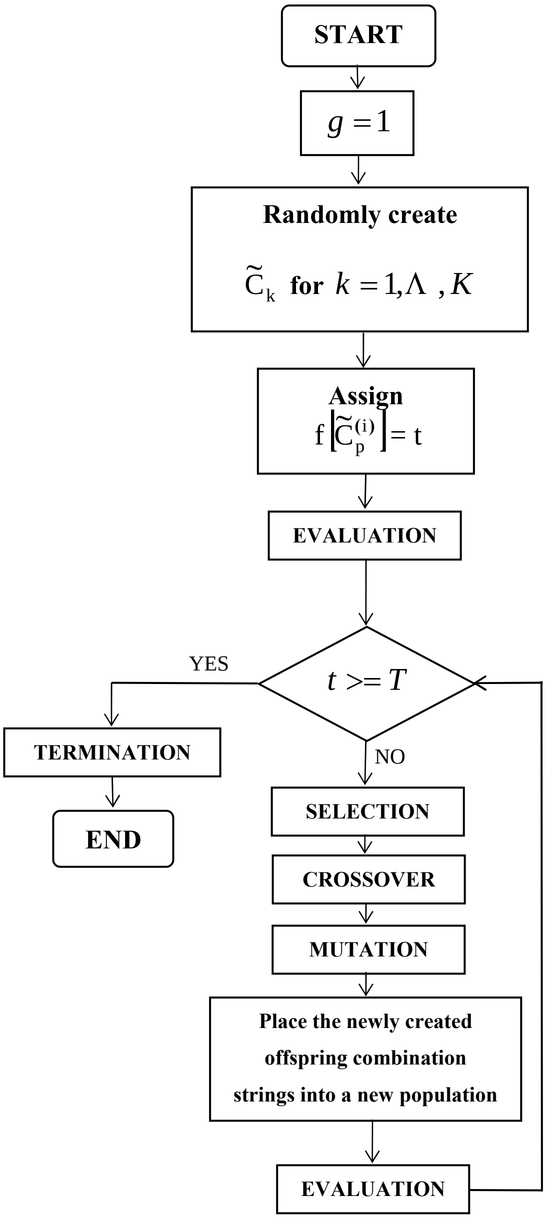

Figure 1: Flowchart depicting the structure of the proposed genetic algorithm used to Channel estimation.

3.4 Crossover

Crossover applies to one or more parents and exchange genetic elements (good or bad) with equal crossover probability between two different strings. This will produce two new strings, which are referred to as offspring. These offspring will constitute the new population of the next generation.

3.5 Mutation

Mutation involves the modification of the value of each solution string with some small probability. The role of mutation is to prevent the premature convergence of the GA to suboptimal solutions. If all the strings in the generation have a bad element at the same location, then further crossover processes between any of these strings will not be able to remove the bad element. In order to skip from this situation, the mutation operation is used. In our proposed method we use two different mutation probabilities for strings and elements.

3.6 Termination

The GA can be terminated if there is no improvement in the maximum fitness value of the population after several iterations. This will ensure with a high probability that the global optimum is found at the expense of high computational complexity and long convergence time. Hence, we terminate the GA of Fig.1 after $f\left[\tilde{C}_p^{(i)}\right]$ is coming upper than a threshold (T). By adjusting the value of T, the bit error rate (BER) performance can be controlled.

TABLE 1
SUMMARY OF VARIOUS PARAMETERS USED IN OUR SIMULATION

Symbol	Description
K=3	Number of users
M=100	Number of data bits per frame
Nc=31	Number of chips per bit
Fd=100HZ	Doppler frequency
ε_k	Average received bit energy of the K-th user
R_b=100 kb/s	Data rate
P=50	Population size
g=20	Number of generation per signalling interval
P_c=0.7	Crossover probability
P_{m1}=0.2	String mutation probability
P_{m2}=0.1	Element mutation probability

4 Simulation Results

In this section, our simulation results are presented in order to demonstrate the performance of the proposed GA based channel estimator. A summary of the various parameters that are used in our simulations is shown in Table 1.

Fig.2 demonstrates the tracking capability of the GA-based CIR estimator. A snapshot of the estimated real and imaginary components of the channel coefficient of a user is compared with its corresponding true value. In order to quantify the channel estimator's performance, the bit error rate (BER) performance between our GA-based channel estimator and conventional correlation-type estimator model has been shown in figure.3. It can be seen that our proposed GA-based channel estimator exhibited a significantly lower BER value than that of the conventional estimator, and its performance was not far from the single-user bound.

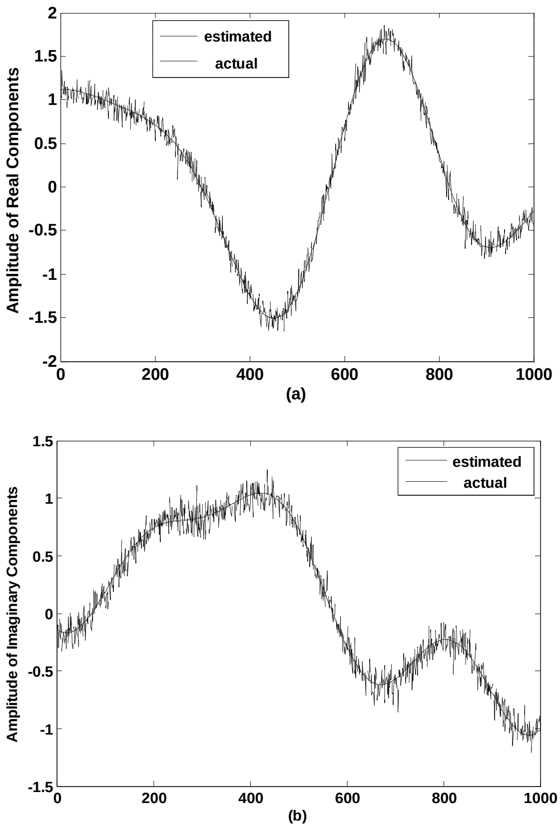

Figure 2: Snapshot of the estimated real (a) and imaginary (b) components of the CIR coefficients corresponding to one user as compared to its true value for Rayleigh-fading channel estimation.

5 Conclusion

In this paper, GAs were developed in order to estimate the CIR coefficients for all users in a symbol-synchronous CDMA system based on the ML decision rule. The system's performance was investigated using computer simulations as a channel estimator with known bits. Our results showed that as a channel estimator, the GA was capable of tracking the variations of the fading channel, while attaining a near-optimum BER performance at different ξ / N_0 values.

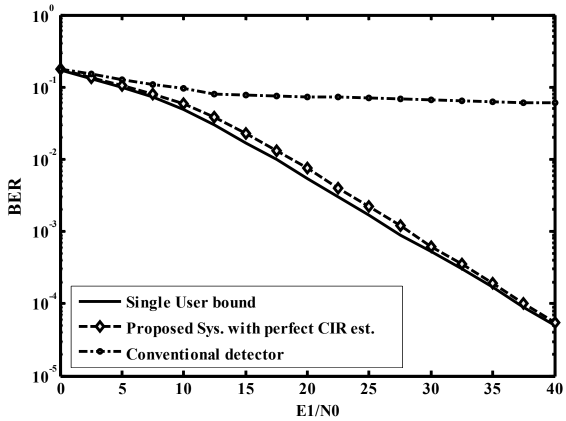

Figure 3: BER performance of the proposed system with GA-based channel estimator for K=3 users, for different value of signal to noise Ratio.

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