UNIVERSITY
OF TRENTO

DEPARTMENT OF INFORMATION AND COMMUNICATION TECHNOLOGY

38050 Povo – Trento (Italy), Via Sommarive 14
http://www.dit.unitn.it

GENETIC ALGORITHM-ASSISTED MAXIMUM-LIKELIHOOD MULTI-USER DETECTION FOR MULTI-RATE MC-CDMA SYSTEMS

C. Sacchi, L. D'Orazio, M. Donelli, R. Fedrizzi, and A. Massa

March 2007

Technical Report DIT-07-008

Genetic Algorithm-assisted Maximum-Likelihood Multi-user Detection for Multi-Rate MC-CDMA Systems

Claudio Sacchi *Member IEEE*, Leandro D'Orazio *Student Member IEEE*, Massimo Donelli *Member IEEE*, Riccardo Fedrizzi, and Andrea Massa *Member IEEE*

University of Trento, Department of Information and Communication Technology (DIT)
Via Sommarive 14, I-38050 Trento (Italy)
Phone: +39-0461-883907, Fax: +39-0461-882093
e-mail: {sacchi, dorazio, donelli, fedrizzi}@dit.unitn.it, andrea.massa@ing.unit.it

Abstract

In this letter[1], the use of Genetic Algorithms (GAs) has been investigated in order to implement a computationally tractable Multi-User Detection (MUD) for synchronous multi-rate Multi-Carrier-Code-Division-Multiple-Access (MR MC-CDMA) systems. It is known that MC-CDMA performances can be seriously limited by multi-user interference. This is particularly true in the case of multi-rate systems where some users could exploit a reduced diversity against multipath channel distortions. The use of Genetic Algorithms (GAs) is therefore proposed as a sub-optimal solution to the MUD problem in a multi-rate Variable-Spreading-Length (VSL) MC-CDMA downlink transmission. A set of selected numerical experiments have been reported and discussed in order to assess the capability of the proposed GA-based approach. The reported results, obtained with an affordable computational burden, have shown a near-optimum behavior of the proposed GA-based MUD.

KEYWORDS: ***Multicarrier modulations, Multi-User Detection, MC-CDMA, Genetic algorithms, Multi-rate transmissions, Multimedia transmission.***

Corresponding author:

CLAUDIO SACCHI, Ph.D.
Assistant professor
University of Trento, Department of Information and Communication Technology (DIT)
Via Sommarive 14, I-38050 Trento (ITALY)
Phone: +39-0461-883907, Fax: +39-0461-882093
E-mail: sacchi@dit.unitn.it

[1] This work has been partially supported by Italian Ministry on Research and University under the framework of the research projects: "Integrated Communication and Navigation" (ICONA) and "Study and Development of Innovative Smart Systems for Highly Reconfigurable Mobile Networks" (project codes: COFIN 2005095303_002 and COFIN 2005099984_001).

1. Introduction

The flow of multimedia traffic through wireless networks is constantly increasing, both in local and in metropolitan areas. Multimedia traffic is characterized by heterogeneous data rates typical of the different streamed media. In this framework, efficient techniques for multi-user and multi-rate data transmission should be investigated. In the case of frequency-selective wireless channels and time-frequency diversity-based transmission techniques, the usual tradeoff between data rate and robustness against channel effects becomes more evident. In a multi-rate context, the diversity gain of higher-data rate transmitters may be reduced with respect to lower-data rate ones. This typically happens in the 3G W-CDMA PHY-layer standard of UMTS (based on DS-CDMA); where variable spreading factors [1] are attributed to various user classes in order to arrange multi-rate services ranging from 15 Kb/s to 960 Kb/s.

Multi-rate transmission can be fairly managed also by 4G Multi-Carrier CDMA (MC-CDMA) schemes by attributing to different user classes a different number of subcarriers and variable-length orthogonal spreading codes [2]. The usual tradeoff between diversity gain and data rate turns on a lower number of subcarriers attributed to the “fastest” users that will be penalized with respect to “slowest” users in terms of channel degradation and multi-user interference (MUI). In such a perspective, multi-rate MC-CDMA performances could be substantially improved by the adoption of multi-user detection (MUD). Theoretical basic concepts about multi-user detection in multi-rate MC-CDMA systems have been thoroughly discussed in [2]. In particular, different MC-CDMA MUD strategies, namely: Maximum Likelihood (ML), Minimum-Mean Squared Error (MMSE) and decorrelating receiver have been analyzed and compared. Best results are obtained by the theoretically-optimum ML-based MUD. The main drawback of this solution consists in the exponential growth of computational burden as the user number increases. For this reasons, authors of [2] suggested the use of MMSE-MUD for practical implementation, as it can provide fairly sub-optimal performance with a reduced computational complexity (polynomially increasing with the user number). In a recent work, Li, Letaief, et al. considered the utilization of a soft sensitive bits algorithm for MAP-based multi-user detection in MC-CDMA systems [3]. The underlying idea is to obtain a “rough” initial estimate of all the user bits using the conventional detector and then identify some specific bit (namely “sensitive bits”) that are most likely to be in errors by means of a devoted metric. Other sub-optimal approaches for MC-CDMA MUD rely on the iterative cancellation of residual multi-access interference coming from the MMSE stage. In [4] Petré, Vandenameele *et.al* proposed a double-stage receiver with a per-carrier Parallel-Interference-Cancellation (pcPIC) put in cascade with a linear MMSE detector. The perfect knowledge of channel state information is assumed in [4]. In [5], iterative joint channel estimation and multi-user detection are proposed for MC-CDMA. The multi-user receiver scheme, similarly to [4], consists of a linear MMSE filter supported by a PIC stage. Differently from [4], channel status information is assumed to be unknown and MUD stages are fed by estimated per-carrier channel coefficients. The channel estimation algorithm considered in [5] is based on an iterative algorithm exploiting Slepian basis expansion. Parallel interference cancellation is often preferred to serial interference cancellation (SIC) due to its short processing delay although its interference suppression effect is inferior. Examples of SIC-based interference cancellation algorithms for MC-CDMA are shown in [6] and [7]. In [7], Tan and Bar-Ness proposed an improvement of MMSE-SIC detection with an equal-BER power control. Such a control mechanism is very useful to increase MUD efficiency in the uplink transmission.

In this letter, the application of Genetic Algorithms (GAs) [8] to multi-rate MC-CDMA multi-user detection is proposed and discussed in order to obtain a near-optimum solution to the ML-MUD problem, reached by spending a reasonable computational effort. The claimed objective is, in particular, to maintain the computational burden of a polynomial order with respect to system parameters. GAs are well known stochastic search methods recently successfully adopted to solve problems related to MC-CDMA systems. Having a look to the recent literature, we should mention the works of Wei and Hanzo [9] and Juntti and Latva-Aho [10] about the application of genetic algorithms to the reception of MC-CDMA signals. Authors of [9] applied the mutation operator to an individual generated by the hard decision made on the output of the maximal-ratio combining (MRC) receiver. In [10], a GA-based supplementary stage is employed in cascade with a MMSE stage driven by a blind channel identification algorithm. The initial population is generated starting from the solution produced by the non-ideal MMSE stage. These two last works deal with fixed-rate MC-CDMA signals, where all users experiment the same diversity gain in the frequency domain. The multi-rate case is of particular technical interest, as the different-rate traffic flows are subjected to different channel degradations involved by the different degrees of diversity exploited in the frequency domain.

In the present work, the use of GAs for a quasi-optimal ML multi-user detection in the multi-rate MC-CDMA has been proposed; the reported numerical results (obtained with a limited computational burden) confirm the capability of the proposed strategy to deal with practical problems related to the use of MC-CDMA systems.

The letter is structured as follows: Section 2 contains a description of the multi-rate MC-CDMA transmission system. Section 3 will describe the GA-based MUD strategy adopted, Section 4 is aimed at showing some selected simulation results and, finally, Section 5 draws letter conclusions.

2. Multi-rate VSL MC-CDMA transmission

Let us consider the multi-rate multi-user MC-CDMA transmission concept illustrated in [2] known as Variable-Spreading-Length (VSL) access. A fixed amount of bandwidth is allocated for downlink transmission. A fixed number of subcarrier N (being N an integer power of 2 in order to simplify the FFT implementation of the VSL transceiver) is available. The transmitting user population is subdivided into "user classes", each one transmitting a digital data stream over a subset of N_m subcarriers, whose cardinality is an integer fractional value of N and depends on the channel bitrate r_m. More in details, M bitrate classes can be defined by the rule [2]: $r_m = 2^{(M-m)} r \;\; m = 1,.., M$, where r=1/T is the bitrate of the "slowest" user class (i.e.: class M), also named *basic data-rate* of the system [2]. The data stream of a user of class m is converted into m parallel outputs. Symbols at each output are copied over $N_m = N/2^{(M-m)}$ branches and then respectively being multiplied by the corresponding bit of spreading codes whose length is N_m. The baseband transmitted signal of the uth user with rate r_m, namely $x_u^{(m)}(t)$, is given as follows:

$$x_u^{(m)}(t) = \sum_{i=1}^{m} A_u^{(m)} D_{u,i}^{(m)} \sum_{n=0}^{N_m-1} c_{u,n}^{(m)} \exp 2\pi j \left\{ \left[(i-1) \frac{N}{2^{(M-m)}} + n \right] \frac{t}{T} \right\} \quad 0 \le t \le T \tag{1}$$

$D_{u,i}^{(m)}$ is the i-th binary BPSK data symbol, $c_{u,n}^{(m)} \in \{-1,1\}$ is the n-th chip of the assigned spreading code, and $A_u^{(m)}$ is the user's u transmitted amplitude. According to [2] and in order to simplify the mathematical formalization of the received signal, we regard a user with rate r_m as $2^{(M-m)}$ effective users at rate r. The decomposition in frequency domain, corresponding spreading codes and spectrum allocation for effective users are pictorially described in fig.1. If U_m denotes the number of users transmitting at rate r_m, the total number of effective users in the system is given by:

$$U = \sum_{m=1}^{M} 2^{(M-m)} U_m \quad m = 1,.., M \tag{2}$$

As the users are transmitting at different bit-rate, we can evaluate the received signal after the duration of $2^{(M-m)}$ symbols of a user with rate r_m. This is given by [2]:

$$y(t)=\sum_{u=1}^{U}\sum_{i=1}^{m}A_u D_{u,i}\sum_{n=0}^{N-1}g_{i,n}c_{u,n}\exp 2\pi j\left\{\left[(i-1)N+n\right]\frac{t}{T}\right\}+z(t) \tag{3}$$

being $g_{i,n}$ the channel gain of the *(i,n)*th subcarrier with normalized squared amplitude expectation, i.e.: $E\left(\left|g_{i,n}\right|^2\right)=1$, and *z(t)* the AWGN with power spectral density N_0.

The received signal *y(t)* is therefore down-converted and the resulting contribution can be expressed in matrix notation:

$$\underline{Y}=\Gamma\Psi\bar{I}\,\underline{D}+\underline{Z} \tag{4}$$

where $\bar{I}$ is a $UNxN$ matrix, obtained by the replicating the UxU identity matrix *I*, Γ is the $NxUN$ channel matrix, and Ψ is the $UNxUN$ diagonal signature matrix of the effective user, defined in [2]. In VLS access, the matrix Ψ contains elements of the Orthogonal Variable Spreading Factor (OVSF) sequence matrix described in [1], completed by zeros in correspondence of spreading codes assigned to users transmitting at higher rates. This implies that symbols coming from "fastest" users involve a reduced amount of MUI.

3. The proposed GA-based multi-user detection for MR VSL MC-CDMA

The optimal MUD in multi-rate MC-CDMA VSL systems is based on the ML criterion [2]. ML-MUD is implemented by minimizing, with respect to the symbols transmitted by the effective users $\hat{\underline{D}}$, the absolute squared error between the received signal and the reconstructed noiseless pattern, i.e. [2]:

$$\hat{\underline{D}}^{opt}=\arg\min_{\underline{D}}\left\{\left(\underline{Y}-\Gamma\Psi I\underline{D}\right)^H\left(\underline{Y}-\Gamma\Psi I\underline{D}\right)\right\} \tag{5}$$

where the superscript operator *H* denotes the complex Hermitian. The channel matrix Γ is supposed here to be completely known. Also, the OVSF code matrix, and therefore Ψ, are assumed to be known by the receiver. Under such hypothesis, the ML-based computation of $\hat{\underline{D}}^{opt}$ is theoretically feasible. The price to be paid is a computational load exponentially growing with the number of the effective users *U*. The effective users' number increases with: a) the number of user classes *M*, and b) the number of orthogonal subcarriers *N*. Fig.1 clearly evidences that the number of effective users is higher than the number of real users. So, the computational burden of theoretical ML detection in the multi-rate case can reach huge amounts that might not be supported by commercial signal processing hardware products.

In this letter, we are proposing a solution based on the use of Genetic Algorithms. Genetic Algorithms are robust, stochastic search methods modelled on the principles of natural selection and evolution [8]. GAs differ from conventional optimisation techniques in that:

a) They operate on a group (namely: *population*) of trial solutions (namely: *individuals*) in parallel. A positive number, namely: *fitness*, is assigned to each individual representing a measure of goodness;
b) They normally operate on a coding of the function parameters (namely: *chromosome*) rather than on the parameter themselves;
c) They use stochastic operators (*selection*, *crossover*, and *mutation*) to explore the solution domain.

The metric of eq.5 is regarded as the fitness of the GA. A set of individuals is encoded with chromosome-like bit strings. The cardinality of the set of individuals is called *population size* [8]. At each iteration, called *generation*, the genetic operators of crossover and mutation are applied to selected chromosomes with probability α_C and α_M respectively, in order to generate new solutions belonging to the search space. The population generation process terminates when the fitness value reaches a given fixed threshold ε or when a fixed number of iterations (namely: *generation number*) are completed. Genetic algorithms have been successfully applied for a wide range of problems characterized by a large number of unknown parameters and highly non-linear behavior [11]. The major advantages of the GAs with respect to the other optimization algorithms, such as gradient conjugate-based methods, are mainly related to their independence from the initialization and their ability to prevent local minima. Moreover it is well known from the scientific literature that it is possible to enhance the convergence ratio making a good choice of the algorithm parameters [8][11]. In particular a proper choice of population size and generation number is mandatory in order to avoid too high computational burden and to keep performances good.

In Fig.2, the flowchart of the proposed GA-assisted ML-MUD detection algorithm is depicted. The initial population consists of P_{pop} individuals obtained starting from the solution $\underline{\hat{D}}^0$ obtained by the hard decision made at the output of a single-user Equal-Gain-Combining (EGC) receiver stage. In particular, we choose to select other individuals as those ones that differ from $\underline{\hat{D}}^0$ by a Hamming distance lower or equal to a maximum given value *dhamm*. The number of the individuals belonging to the so-generated population can be obtained as: $P_{pop} = \sum_{p=0}^{dhamm} \binom{U}{p}$. Such a criterion has been considered in order to provide a good choice of the initial population without spending a relevant computational effort. In [9], the initial population is generated by a stochastic mutation of the hard decision made on the output of a MRC stage. In our opinion, such a choice might be not very suitable in the presence of high level of MUI. In fact, it is known by literature that MRC is the optimal combining methodology in the single-user case, but its performances rapidly deteriorate when the number of simultaneous users increases (see e.g. results shown in [12] that evidenced a worst behaviour of MRC with respect to EGC in case of increasing level of MUI). The initialization strategy proposed in this letter is very similar to the one considered in [10], where the initial population was generated among the elements differing by *dhamm* from an initial solution obtained by a MMSE-MUD stage. In our opinion, such a last choice may theoretically perform better than ours. But, from a more practical viewpoint, the MMSE-MUD implementation would involve the inversion of a big *NxN* matrix $\left(\Gamma\Psi\bar{\mathbf{I}}\Psi^{H}\Gamma^{H} + N_0\mathbf{I}\right)$ that might be not a trivial task. EGC combining is very simple in case of perfect knowledge of the channel matrix and would not significantly affect the computational burden of the entire receiver chain. After the initialization, a fitness value is associated to the P_{pop} individuals by computing the metric of eq.5. At each generation, GA stochastic operators [8] are applied in order to evolve the population. Selection is performed by analyzing two individuals and choosing the one with the best value of the fitness. Cross-over is applied on solutions belonging to the search space with an assigned probability α_C. The cross-over strategy adopted here is the *uniform* crossover [8], in which an individual is created by randomly choosing the *i*th bit of the new generated solution among the *i*th bit present in one of the two selected parents. The mutation operator is applied by change a bit of the selected individual with an assigned probability α_M. Furthermore we use elitism [8] in order to maintain the best individual from the generation j to the next generation j+1. The population generation terminates when a satisfactory solution has been produced or when a fixed number of iterations, J_{gen} has been completed.

4. Experimental results

In order to assess the proposed GA-based MUD algorithm, some selected simulation trials have been performed by using an equivalent baseband simulator of a multi-rate MC-CDMA downlink transmission system. Simulations have been performed in MATLAB-SIMULINK 7.0.1 environment. In order to define more realistic simulation trials, the multipath fading channel modelling and parameterization has been performed through some experimental data reported in [13] and related to 1.95 GHz 3GPP transmission scenarios. In particular, a 4-paths Rayleigh fading channel related to an urban vehicular scenario has been simulated by using a tapped delay line with coherence bandwidth equal to 1.25MHz and Doppler spread equal to 125 Hz. The users' amplitudes A_u have been chosen in order to maintain the per-bit signal-to-noise ratio E_b/N_0 equal for all user classes [2]. The simulated multi-rate MC-CDMA configuration employs N=16 orthogonal subcarriers in order to allow M=3 user classes to transmit at data rates equal to 1024 Kb/s (class 1), 512 Kb/s (class 2), and 256 Kb/s (class 3). The effective processing gains of the different user classes are: N_1=4, N_2=8, and N_3=16 respectively. We considered the maximum user load allowed by the OVSF spreading code attribution, i.e.: U=16 effective users corresponding to $U_1=1$ users of class 1, $U_2=2$ users of class 2, $U_3=8$ users of class 3.

As far as the parameterization of the GA optimizer is concerned, we firstly selected crossover probability α_C and mutation probability α_M equal to 0.9 and 0.01, respectively. This setting is reasonable because α_C is the index of the "evolutionary capability" of the GA, whereas a high value of α_M would turn the GA into a kind of random search [11]. In the absence of specific analytical selection criteria [8] [11], the generation number J_{gen} and the population size P_{pop} (depending on the parameter *dhamm*, as mentioned in Section 3) have been chosen by means of preliminary experimental trials explicitly devoted to. We have considered in these simulations the heuristic selection criteria enunciated in [11]: a) the population size should be sufficiently large in order to have a conveniently-dimensioned space search; b) the number of generations should be appropriately assigned in dependence of the population size. In fact, in case of large population, too strict limit for the search time can force algorithm to stop without having enough time to realize its search possibility [11]. The test was performed considering E_b/N_0 equal to 15dB. As final results of such preliminary simulation trials, we derived a reasonable choice of the GA parameterization keeping into account the usual tradeoff between computational complexity and achieved performances. In particular, we selected J_{gen}=10 and *dhamm*=2, corresponding to a value of P_{pop}=137.

In Figs. 3-4-5, curves drawing the average BER results vs. E_b/N_0 achieved by the proposed GA-assisted ML detection are shown for users belonging to class 1, class 2 and class 3 respectively, and compared with corresponding results yielded by the following MC-CDMA detection schemes (the ideal knowledge of the channel state information has been supposed in all the simulations performed):

- Single-stage per-user linear MMSE-MUD [2][12];
- Two-stage detection scheme proposed in [4] (and, similarly, in [5]), consisting of a per-user linear MMSE stage followed by a Per-Carrier Parallel Interference Cancellation (pcPIC) stage. The N contributions provided as output by the pcPIC stage are then combined by using the MRC criterion;
- Linear MMSE receiver followed by a Successive Interference Cancellation (SIC) stage, as described in [6] and [7]. The MMSE SIC is based on a per-user successive decoding with an arbitrary, but fixed order. In the multi-rate VSL MC-CDMA context, we can assume that users are received starting from the slower to arrive to the faster.
- Curves of the single-user bound achieved for the different users classes. The single-user bound has been derived by simulating a single-user MC-CDMA system (therefore interference-free) using a number of subcarriers equal to effective processing gain of the intended class (N_1=4 for the class 1, N_2=8 for the class 2 and N_3=16 for the class 3). The output of the coherent FFT demux is then combined on the basis of the MRC criterion that is the optimal (ML-based) criterion in the case of single-user transmission.

We can note that the GA-assisted ML-MUD performs better than sub-optimum MMSE, MMSE-pcPIC and MMSE-SIC MUD algorithms for all the considered user classes. In particular, the proximity of the related BER curve to the single-user bound is dramatically evident in Fig.3. As the users' data rate decreases and, therefore, the processing gain increases, the single-user bound trends to depart from all sub-optimal algorithms. This is not unexpected, because the single-user bound drawn in Figs.3-5 is actually a lower bound also on theoretically-optimal ML-MUD, as stated in [2]. However, if we take a look to BER curves of Fig.4 and Fig.5, we can note that the performance improvement yielded by GA-assisted ML-MUD even becomes more relevant. It is worth noting that that BER performances of MMSE-pcPIC and MMSE-SIC algorithms drawn in Fig.5 for user class 3 are almost coincident. This is due to the successive cancellation order followed in our simulations.

As far as computational issues are concerned, Tab.1 shows the order of computational complexity for each MUD algorithm assessed (second column), the number of elementary operations required by each algorithm to derive a sub-optimal solution to the considered problem (third column), and finally in the fourth column, the number of elementary operations normalized with respect to the corresponding value required by the theoretical ML-MUD exploring the full search space (equal to 2^U [2]). The reader can note that the computational burden of the proposed GA-assisted ML-MUD increases only by less than one order of magnitude with respect to that one required by MMSE-MUD and is slightly reduced with respect to MMSE-pcPIC and MMSE-SIC. In the last column of Tab.1, the noticeable reduction of computational effort with respect to theoretical ML-MUD is clearly shown. If the number of effective users U increased, such a computational saving would be even more glaring.

5. Conclusion

In this letter, the use of genetic algorithms (GAs) has been proposed in the context of the multi-user detection (MUD) of multi-rate Variable-Spreading-Length (VSL) MC-CDMA signals transmitted over mobile downlink channels. Results shown evidenced a promising quasi-optimal behaviour of the proposed GA-based MUD algorithm, provided that GA parameters are carefully tuned. The performance improvement achieved with respect to state-of-the-art interference cancellation schemes is clearly demonstrated. Such relevant results have been achieved by spending an affordable computational burden. Future works could concern with some relevant aspects not faced in the present paper, like e.g. effects of non-ideal channel estimation, effects of system nonlinearities, joint GA-based channel estimations and symbol detection, etc.

References

[1] E. Dahlman, P. Beming, J. Knutson, F. Ovesjo, M. Persson, and C. Roobol, "W-CDMA – The Radio Interface for Future Mobile Multimedia Communications", *IEEE Trans. on Veh. Technol.*, vol.47, no.4, pp.1105-1118, Nov.1998.

[2] P-W Fu, and K-C. Chen, "Multi-Rate Multi-Carrier CDMA with Multiuser Detection for Wireless Multimedia Communications", *Proc of 2003 IEEE Wireless Commun. and Networking Conf.(WCNC 2003),* New Orleans (LA) , March 16-20, 2003, vol.1, pp.385-390.

[3] J. Li, K.B. Letaief, and Z. Cao, "Reduced Complexity MAP-Based Iterative Multiuser Detection for Coded Multicarrier CDMA Systems", *IEEE Trans. Comm.,* vol.52, no.11, pp. 1909-1915, Nov. 2004.

[4] F. Petré, P. Vandenameele, A. Bourdoux, B. Gyselincks, M. Engels, M. Moonen, and H. De Man, "Combined MMSE/pcPIC multiuser detection for MC-CDMA", *Proc. of IEEE 51st Conf. on Vehicular Tech. 2000 (VTC-Spring 2000),* Tokyo (JP), May 15-18, 2000, vol.2, pp.770-774.

[5] T. Zemen, C.F. Mecklembraucker, J. Wehinger, and R.R. Muller, "Iterative Joint Time-Variant Channel Estimation and Multi-User Detection for MC-CDMA", *IEEE Trans on Veh. Technol.*, vol.5, no.6, pp. 1469-1478, Jun. 2006.

[6] V. Kuhn, "Iterative Interference Cancellation and Channel Estimation for Coded OFDM-CDMA", *Proc. of 2003 IEEE Int. Conf. on Commun. (ICC 2003).*, Anchorage (AK), vol. 4, May 2003, pp. 2465–2469.

[7] M. Tan, and Y. Bar-Ness, "Equal BER Power Control for Uplink MC-CDMA with MMSE Successive Interference Cancellation", *IEEE Comm. Letters*, vol.8, no.6, pp. 348-350, Jun. 2004.

[8] D.E. Goldberg*, Genetic Algorithms in Search, Optimization and Machine Learning*, Addison-Wesley, Reading, MA: 1999.

[9] H. Wei, and L. Hanzo, "Reduced-Complexity Near-Optimum Genetic Algorithm Assisted Multiuser Detection for Synchronous Multicarrier CDMA", *Proc. of 59th IEEE Veh. Technol. Conf. 2004 (VTC Spring – 2004)*, Milan (I), May 17-19, 2004, vol.3, pp. 1717-1721.

[10] Z. Li, M.J. Juntti, and M. Latva-Aho, "Genetic Algorithm Based Frequency Domain Multiuser Detection for MC-CDMA Systems", *Proc. of 61st IEEE Veh. Technol. Conf. 2005 (VTC-Spring - 2005)*, Stockholm (S), May 30 2005, vol. 2, pp. 983-987.

[11] Y.R. Tsoy, "The Influence of Population Size and Search Time Limit on Genetic Algorithm", *Proc. of the 7th Korea-Russia International Symposium on Science and Technology (KORUS 2003)*, Uslan (KOR), Jun. 28-Jul. 6 2003, vol. 3, pp. 181-187.

[12] S. Hara, R. Prasad, "Overview of multicarrier CDMA", *IEEE Comm. Mag.*, pp.126-133, Dec. 1997.

[13] *"3rd Generation Partnership Project;Technical Specification Group Radio Access Network; UE Radio Transmission and Reception (FDD) (Release 5)"*, ETSI Technical Report 3GPP TS 25.101, v5.5.0, December 2002.

Figure Captions

Fig.1. Pictorial illustration of the concept of effective users in VSL MC-CDMA multi-rate access.

Fig.2. Flowchart of the proposed GA-assisted ML-MUD algorithm.

Fig.3. BER results vs. E_b/N_0 provided by the different MUD algorithms assessed (GA-assisted ML-MUD, MMSE, MMSE-PIC, MMSE-SIC) and by the single-user bound: user class #1 (N_1 = 4, r_{b1} = 1024 Kb/s) urban 3GPP vehicular channel, J_{gen} = 10, *dhamm* = 2.

Fig.4. BER results vs. E_b/N_0 provided by the different MUD algorithms assessed (GA-assisted ML-MUD, MMSE, MMSE-PIC, MMSE-SIC) and by the single-user bound: user class #2 (N_2 = 8, r_{b2}=512 Kb/s) urban 3GPP vehicular channel, J_{gen} =10, *dhamm*=2.

Fig.5. BER results vs. E_b/N_0 provided by the different MUD algorithms assessed (GA-assisted ML-MUD, MMSE, MMSE-PIC, MMSE-SIC) and by the single-user bound: user class #3 (N_3 = 16, r_{b3} = 256 Kb/s) urban 3GPP vehicular channel, J_{gen} = 10, *dhamm* = 2.

Table Captions

Tab.1 Analysis of computational complexity of the different MUD algorithms assessed.

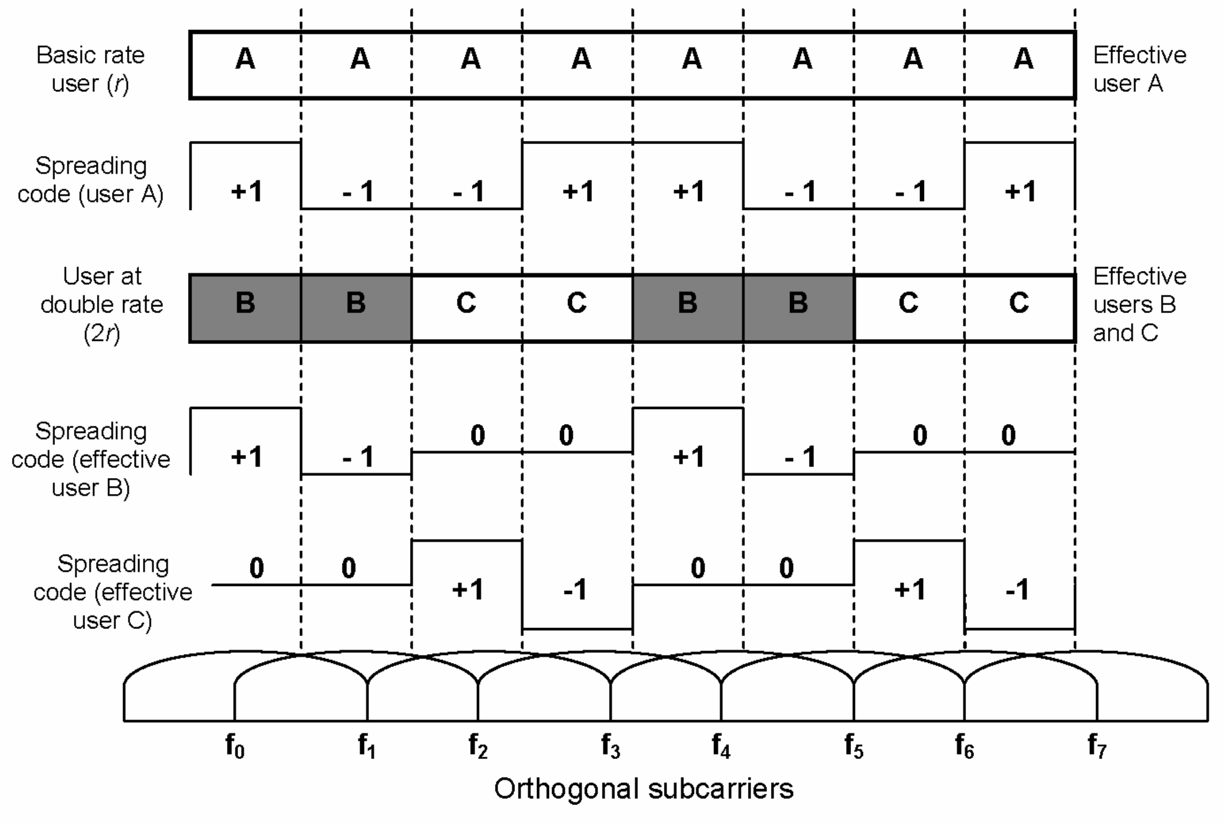

Figure 1 (C. Sacchi, L. D'Orazio, *et.al.*)

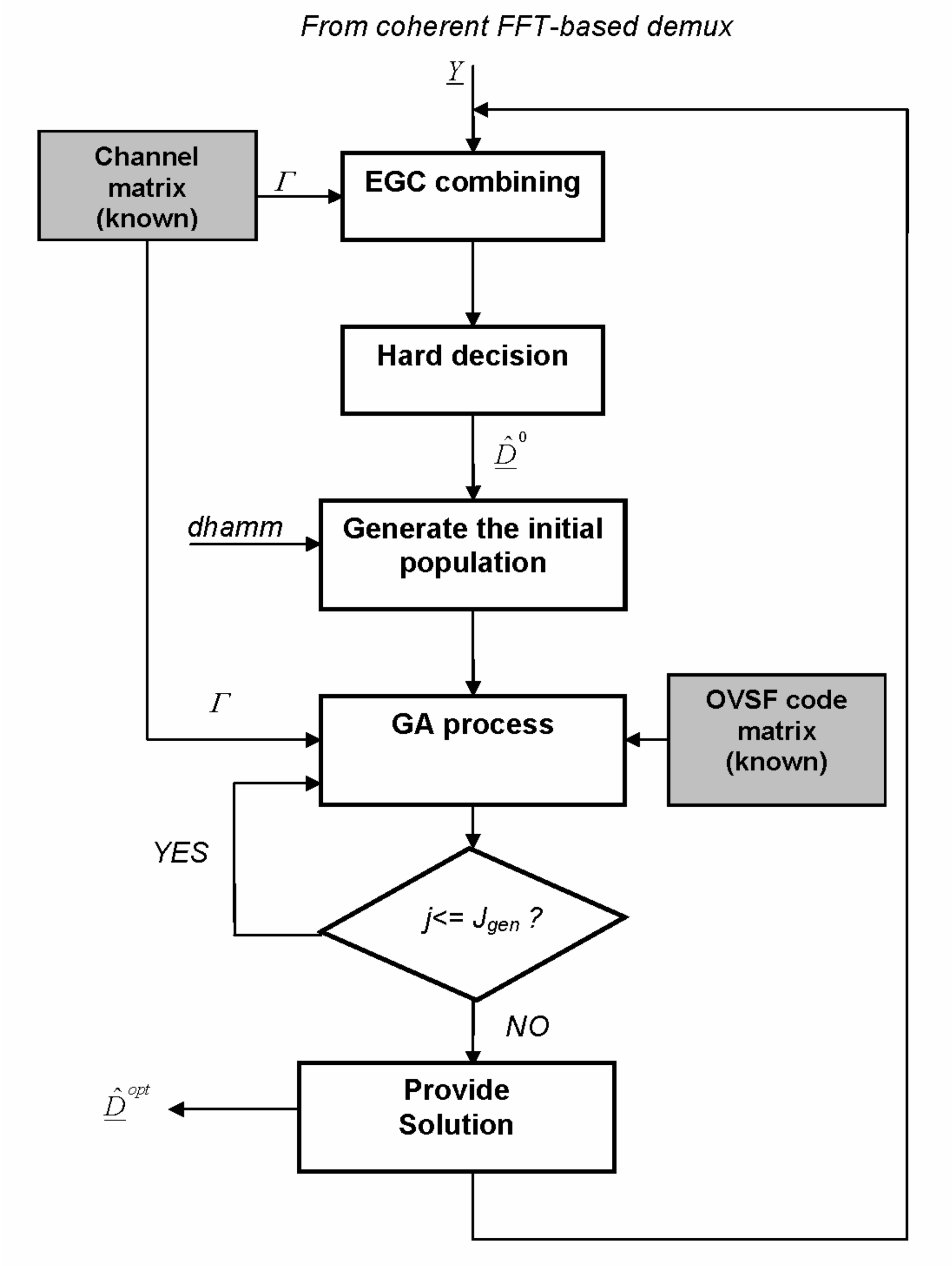

Figure 2 (C. Sacchi, L. D'Orazio, *et.al.*)

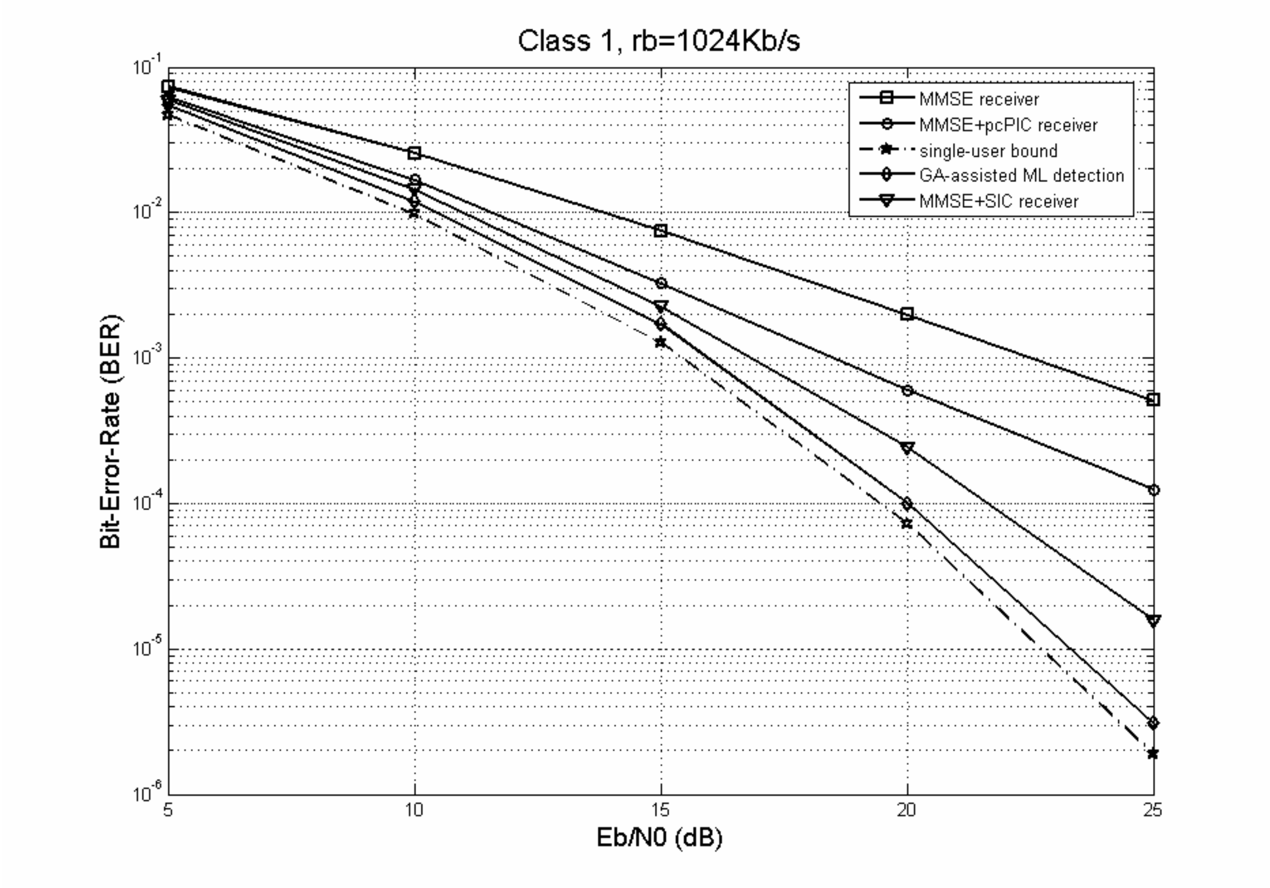

Figure 3 (C. Sacchi, L. D'Orazio, *et.al.*)

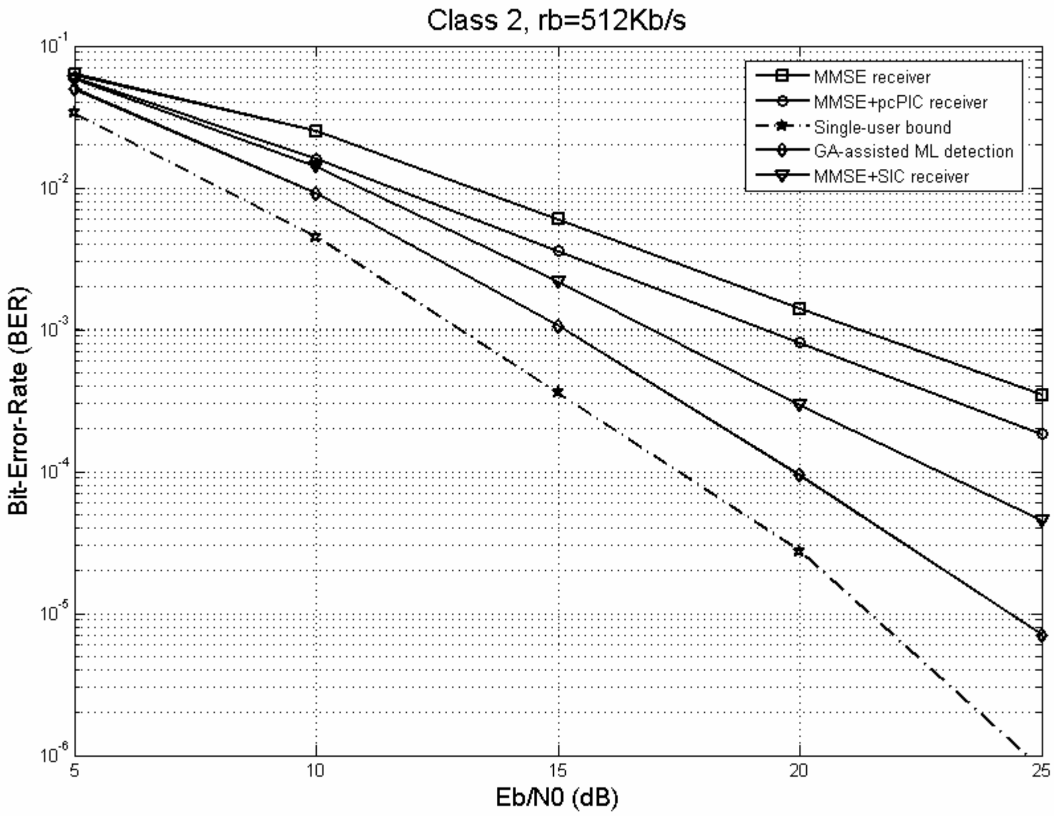

Figure 4 (C. Sacchi, L. D'Orazio, *et.al.*)

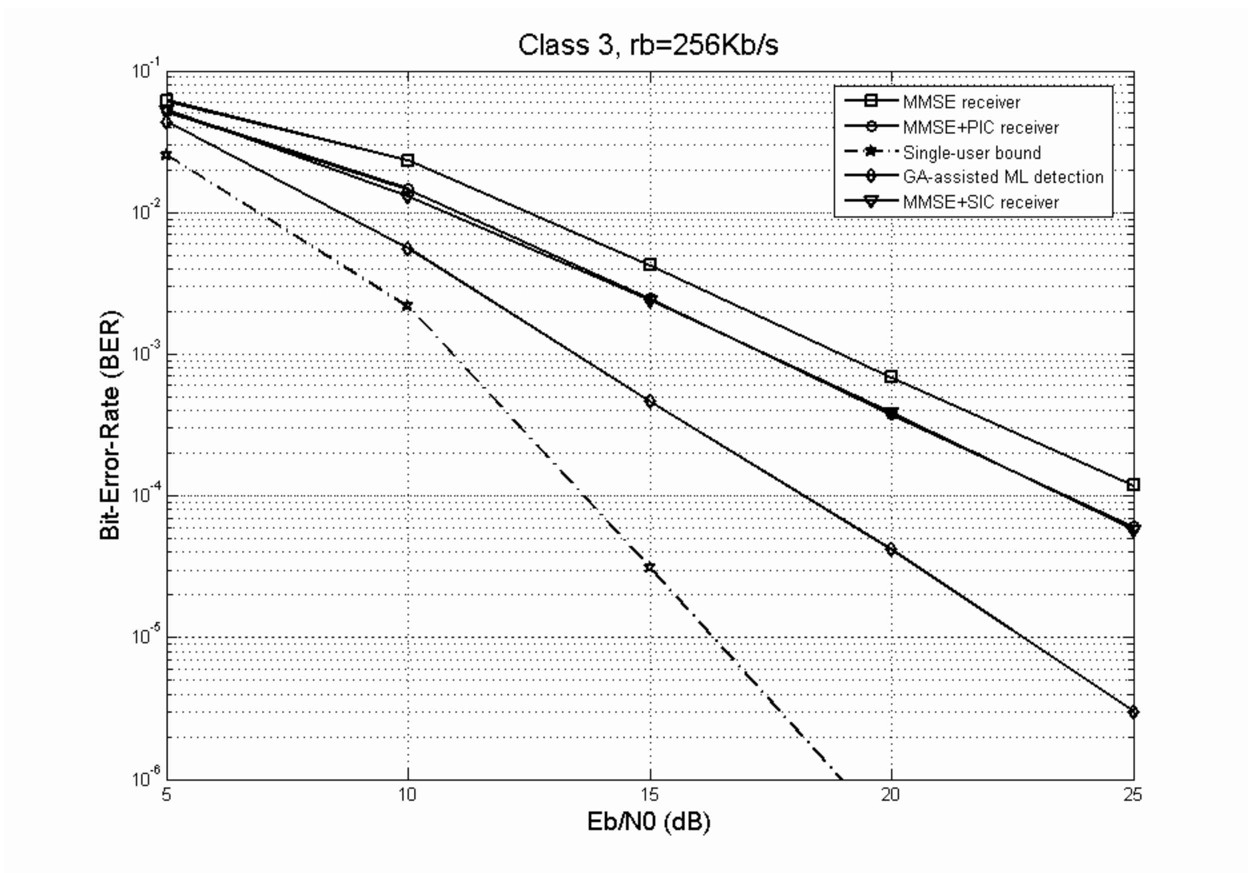

Figure 5 (C. Sacchi, L. D’Orazio, *et.al.*)

MUD ALGORITHM ASSESSED	ORDER OF COMPUTATIONAL COMPLEXITY	# OF ELEMENTARY OPERATIONS NEEDED TO COMPUTE THE PROBLEM SOLUTION	# OF ELEMENTARY OPERATIONS NEEDED TO COMPUTE THE PROBLEM SOLUTION NORMALIZED WITH RESPECT TO THEORETICAL ML-MUD
GA-assisted ML detection	$N + P_{pop} + (\alpha_C + \alpha_M) J_{gen} P_{pop}$	$1.4\text{x}10^3$ (J_{gen}=10, P_{pop}=137, α_C=0.9, α_M=0.01)	$2.1\text{x}10^{-2}$
MMSE [12]	UN	$2.56\text{x}10^2$	$3.9\text{x}10^{-3}$
MMSE-pcPIC [4]	$U^2 N$	$4.1\text{x}10^3$	$6.25\text{x}10^{-2}$
MMSE-SIC [6-7]	$U^2 N$	$4.1\text{x}10^3$	$6.25\text{x}10^{-2}$

Table 1 (C. Sacchi, L. D'Orazio, *et.al.*)