Table 3: RI systematic circulant linear 1/2 rate ring-BCM schemes using 4QAM 8-dimensional signal set

n	1/2 rate ring-BCM schemes, 4QAM 8-dimensional signal set	$d^2_{E_c}$	ACG, over BPSK (dB)	N
8	12 8 14 15	32.0	6.02	20
10	8 13 14 15 15	40.0	6.98	60
12	10 12 9 15 3 0	48.0	7.78	396

Table 4: RI pseudocyclic 1/2 rate ring-BCM schemes using 4QAM 8-dimensional signal set

n	1/2 rate ring-BCM schemes, 4QAM 8-dimensional signal set	$d^2_{E_c}$	ACG, over BPSK (dB)	N
10	13 15 12 15 15 7 0 0 0 0	40.0	6.98	110
12	11 8 10 7 1 14 15 0 0 0 0 0	48.0	7.78	456

It is interesting to note that the circulant schemes offer the same ACG as the pseudocyclic schemes, but with significantly fewer nearest neighbours.

For all the cases, equivalent NRI schemes with similar distance properties were also found, with the same performance as the corresponding RI schemes, so the latter only are listed, as they are more useful in practice. Fig. 2 shows the performance of the bit error rate for the (12, 8) (3 1 7 7 4 2 1 0) RI systematic circulant linear ring-BCM scheme (Table 1) for the 4QAM 4-dimensional signal set, in comparison with BPSK. Decoding is performed using a versatile soft decision decoder, based on the Chase algorithm [7].

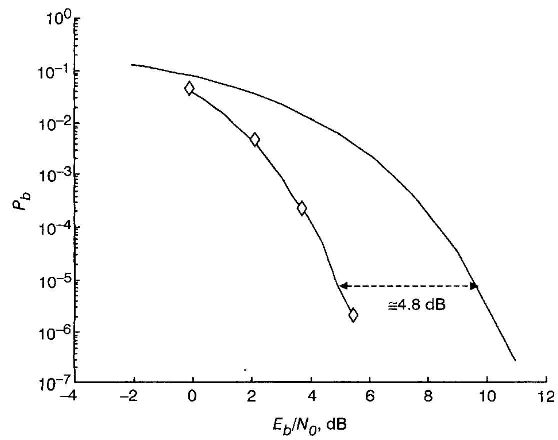

Fig. 2 *Bit error rate for (12, 8) (3 1 7 7 4 2 1 0) RI systematic circulant ring-BCM scheme (Table 1) for 4QAM 4-dimensional signal set, in comparison with BPSK (AWGN channel)*

——— BPSK

–◇–◇– (12, 8) (3 1 7 7 4 2 1 0) RI systematic circulant ring-BCM scheme

Conclusions: The proposed signal set for combined coding and modulation schemes is designed by expanding the biorthogonality of Walsh-Hadamard waveforms using 4QAM. The advantages of a two-dimensional modulation and the inherent use of coding in the Walsh-Hadamard biorthogonal signal set are combined to provide the improved distance properties and performance of the new scheme. 4QAM 4-dimensional signal set ring-BCM schemes designed for this constellation show asymptotic coding gains of up to 6.02 dB. 4QAM 8-dimensional signal set ring-BCM schemes offer up to 7.78 dB. Though this performance will be reduced somewhat due to the effect of the relatively large number of nearest neighbours (since the code distance profile is very uniform), it is better than that of equivalent MPSK ring-BCM schemes by about 2 to 3 dB.

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J. Castiñeira Moreira (*Electronic Department, School of Engineering, Mar del Plata University, J. B. Justo 4302, Mar del Plata, 7600, Argentina*)

E-mail: casti@fi.mdp.edu.ar

B. Honary and P.G. Farrell (*Department of Communication Systems (DCS), Lancaster University, Lancaster, LA1 4YR, United Kingdom*)

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TTCM assisted genetic-algorithm aided reduced-complexity multiuser detection

S.X. Ng, K. Yen and L. Hanzo

Turbo trellis coded modulation assisted genetic-algorithm aided reduced-complexity multiuser detection (TTCM-GA-MUD) is capable of providing a considerable coding gain of 2.9 dB without any bandwidth expansion at a bit error ratio of 10^{-4}, while maintaining a complexity reduction factor 8.59×10^6 compared to the optimum multiuser detector in the context of 16QAM transmissions, while supporting $K = 10$ users.

Introduction: The optimal code division multiple access (CDMA) multiuser detector (MUD) [1] based on the maximum-likelihood (ML) detection rule performs an exhaustive search of all the possible combinations of the K number of users' M-ary symbol sequences and then selects the most likely combination from the set of M^K legitimate combinations as the K-component M-ary detected symbol sequence. Since an exhaustive search is conducted, the computational complexity of the detector increases exponentially with the number of users K as well as with the number of phasors in the modulation constellation employed. Genetic algorithms (GAs) have been used for efficiently solving combinatorial optimisation problems in numerous applications [2]. Recently, GA assisted MUD (GA-MUD) has been studied using binary phase shift keying (BPSK) modulation in the context of a CDMA system [3, 4], which exhibits a substantially reduced complexity compared to the optimum MUD, while maintaining a similar performance. Turbo trellis coded modulation (TTCM) [5] is a channel coding scheme, which has a structure similar to that of the family of power efficient binary turbo codes, but avoids extending the required bandwidth by absorbing the parity bits upon extending the phasor constellation.

TTCM-GA-MUD: We consider a synchronous CDMA uplink system as shown in Fig. 1, where K users simultaneously transmit data packets of 1000 TTCM encoded symbols using M-ary modulation to a MUD over AWGN channels. The TTCM scheme employed a code memory of three and four turbo decoding iterations. The received signal can be written as: $r(t) = s(t) + n(t)$, where $s(t)$ is the sum of the transmitted signals of all users and $n(t)$ is the zero-mean complex AWGN with independent real and imaginary components, each having a double-sided power spectral density of $\sigma^2 = N_0/2$. It can be shown that the log-likelihood function (LLF) for a vector $\boldsymbol{b}$ is given by [1]:

$$\mathrm{LLF}(\boldsymbol{b}) = -\frac{1}{2\sigma^2}\int_0^{T_b}|r(t)-s(t)|^2 dt = -\frac{1}{2\sigma^2}\left\{\int_0^{T_b}|r(t)|^2 dt - \Omega(\boldsymbol{b})\right\}$$

where $\Omega(\boldsymbol{b}) = 2\Re[\boldsymbol{b}^H\boldsymbol{C}^*\boldsymbol{Z}] - \boldsymbol{b}^H\boldsymbol{C}^*\boldsymbol{R}\boldsymbol{C}\boldsymbol{b}$, $\boldsymbol{R}$ is the $(K \times K)$-dimensional user signature sequence cross-correlation matrix of the K different signature sequences $a_k(t)$, $k \in \{1, \ldots, K\}$, $\boldsymbol{Z}$ is the output vector of the matched filters, $\boldsymbol{b} = [b_1, \ldots, b_K]^T$ is the complex K-component M-ary symbol vector of the K users, and $\boldsymbol{C}$ is the complex channel impulse response vector of the links between the transmitters and receiver. More specifically, for transmission over a non-dispersive AWGN channel, $\boldsymbol{C}$ is a diagonal unity matrix. The notations $(\cdot)^H$ and $(\cdot)^*$ represent the complex conjugate transpose and complex conjugate of the matrix $(\cdot)$, respectively.

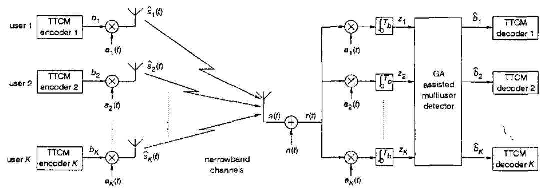

Fig. 1 *Block diagram of K-user synchronous CDMA uplink model*

The decision rule for the optimum-MUD scheme based on the ML criterion is to choose the specific M-ary symbol combination $\boldsymbol{b}$ from the set of M^K possible combinations of the K number of M-ary users, which maximises the correlation metric $\Omega(\boldsymbol{b})$, yielding $\hat{\boldsymbol{b}} = \arg\{\max_{\boldsymbol{b}}[\Omega(\boldsymbol{b})]\}$. Here, the optimum decision vector $\hat{\boldsymbol{b}}$ represents the *hard decision* values for a specific K-symbol combination of the K users during an M-ary symbol period. Based on the *hard decision* vector component $\hat{b}_k$ of vector $\hat{\boldsymbol{b}}$, we derived the log-likelihood channel metrics for the kth user's TTCM decoder for all the M possible M-ary modulated symbols as:

$$P_{k,m}(\hat{b}_k \mid b_{k,m}) = -\frac{|\hat{b}_k - b_{k,m}|^2}{2\sigma^2}$$

where $b_{k,m}$ is the mth phasor in the constellation space and $m \in \{0, \ldots, M-1\}$. Note that it is possible to obtain the *soft decision* metrics for the optimum-MUD, although its employment imposes a higher complexity. Specifically, given $r(t)$ and all possible $\mathrm{LLF}(\boldsymbol{b})$ values, we derived the *soft decision* metrics as:

$$P_{k,m}(r(t) \mid b_{k,m}) = \ln\left\{\sum_{(\text{if } b_{k,m}=b_k)}^{(\text{all possible } \boldsymbol{b})} \exp(\mathrm{LLF}(\boldsymbol{b}))\right\}$$

Our proposed reduced-complexity TTCM-GA-MUD scheme employed the *hard decision* metric and performed only a partial search, rather than full search, using the objective function of $\exp(\Omega(\boldsymbol{b}))$. The configuration of the GA employed in our system is shown in Table 1. For a detailed description of the GA-MUD, readers are referred to [3]. In general, the detection complexity of the GA-MUD is governed by the required number of GA generations Y and populations P, which ensure a reliable decision. The computational complexity of the GA, quantified in the context of the total number of objective function evaluations is related to $P \times Y$.

Table 1: Configuration of TTCM-GA-MUD employed in our system

Setup/parameter	Method/value
Selection method	Fitness-proportionate
Crossover operation	Uniform crossover
Mutation operation	Standard binary mutation
Elitism, incest prevention	Yes
Population size P	KM
Mating pool size T	$T \le P$
Probability of mutation p_m	0.1
Termination generation Y	$(1/2)KM$
M-ary modulation M	4(QPSK), 16(16QAM)
Spreading factor	31 chips
TTCM interleaver length	1000 symbols

Simulation results: We found (although not explicitly shown here due to lack of space) that for detecting K users each employing M-ary modulation, the rule of thumb quantifying the required complexity of the TTCM-GA-MUD scheme is given by $P \times Y \simeq (1/2)K^2M^2$, where $P \simeq KM$ and $Y \simeq (1/2)KM$, which attains a performance similar to that of the optimum MUD. Hence, the computational complexity reductions obtained by the TTCM-GA-MUD compared to that of the optimum MUD can be construed to be about $F = M^K/((1/2)K^2M^2) = 2M^{K-2}K^{-2}$. For the specific example of $K = 10$ and $M = 16$, the complexity reduction factor F was 8.59×10^6.

Fig. 2 shows the bit error ratio (BER) against signal-to-noise ratio per bit, namely E_b/N_0, performance of the TTCM-GA-MUD and that of the TTCM-optimum-MUD schemes, when communicating over AWGN channels using both quadrature-PSK (QPSK) and 16-level quadrature amplitude modulation (16QAM) TTCM. Fig. 2 also shows that the optimum-MUD exhibits $\simeq 0.3$ dB performance loss both in conjunction with *hard* and *soft decisions*, when K increased from one to four. At $K = 10$, the performance loss of TTCM-GA-MUD is about 1 and 3 dB, as shown in Fig. 2, compared to the TTCM-assisted single user schemes employing *hard* and *soft decisions*, respectively, regardless whether QPSK or 16QAM modulation schemes were used.

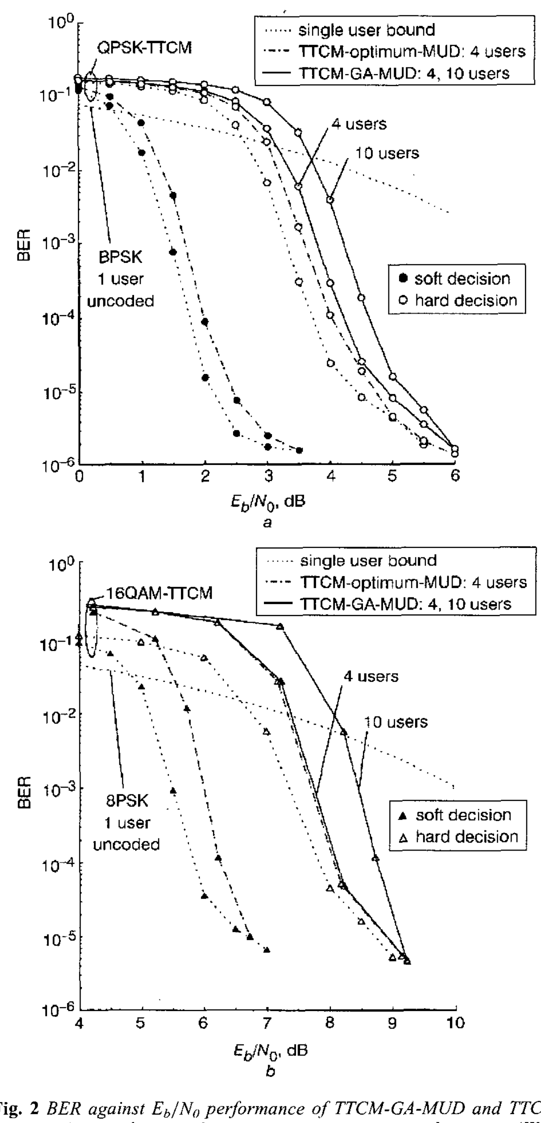

Fig. 2 *BER against E_b/N_0 performance of TTCM-GA-MUD and TTCM-optimum-MUD schemes, when communicating over non-dispersive AWGN channels*

a Effective throughput 1 bit/symbol
b Effective throughput 3 bit/symbol

Conclusions: We have proposed a reduced-complexity TTCM-GA-MUD scheme that is capable of maintaining a performance similar to that of the optimum-MUD. For $K = 10$ users and a BER of 10^{-4}, the TTCM-GA-MUD aided QPSK and 16QAM systems achieved an SNR reduction of 3.8 and 2.9 dBs at the effective throughputs of 1 and 3 bit/symbol in comparison to the single user bounds of uncoded BPSK and uncoded 8-level PSK (8PSK), respectively, without extending the required bandwidth. The complexity reduction factors of $F = 1.31 \times 10^3$ and $F = 8.59 \times 10^6$ were achieved for $M = 4$ and $M = 16$, respectively, when supporting $K = 10$ users.

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S.X. Ng, K. Yen and L. Hanzo (*Department of Electronics and Computer Science, University of Southampton, Southampton SO17 1BJ, United Kingdom*)

E-mail: lh@ecs.soton.ac.uk

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Learning of physical-like sound synthesis models by adaptive spline recurrent neural networks

F. Iannelli and A. Uncini

A recently introduced neural networks architecture, 'adaptive spline neural networks' with FIR/IIR synapse, is used to define a general class of physical-like sound synthesis model. To reduce computational cost, use is made of power-of-two synapses followed by a CR-spline-based flexible activation function the shape of which can be modified through its control points. The learning phase is performed by an efficient combinatorial optimisation algorithm, Tabu Search, for both power-of-two weights and CR-spline control points.

Introduction: The physical model paradigms are in general based on the subdivision of the synthesiser in a nonlinear excitation part in connection with other linear parts as delay lines and/or filters. The most famous model-based technique is the so-called digital waveguide filter [1]. One of the main problems with model-based synthesis techniques is the determination of the model parameters. Usually, several analyses of the original signal are necessary to design the filters correctly, and many simplifications are made to describe the nonlinear excitation mechanism (NLEM). The NLEM, in fact, is very important in so far as it characterises the timbre of the instrument.

In this Letter we propose a new recurrent-network-based synthesis model for single reed NLEM. Recently, a neural networks architecture, based on a flexible Catmul-Rom spline (CR-spline) activation function, the so-called 'adaptive spline neural networks' (ASNNs), has been proposed [2]. ASNNs have universal approximation property and are very suitable for many nonlinear signal processing applications. In general, the NLEM, as in the vibrating reed, is a nonlinear system with memory, so a static network cannot adequately model this system. To take this nonlinear dynamic into account, neural networks with FIR/IIR synapse and flexible activation function are used [2, 3]. Moreover, to obtain an efficient hardware/software implementation, the synaptic weights are constrained to be power-of-two terms.

The learning phase has been carried out by an efficient combinatorial optimisation algorithm, the so-called Tabu Search, recently used for a power-of-two adaptive filter [4].

To demonstrate the effectiveness of the proposed model, experiments on single-reed woodwind instruments have been carried out.

Physical-like synthesis model: A model for a woodwind instrument is shown in Fig. 1. It is composed of a delay line, a linear element (filter) and an NLEM [1]. The single-reed and mouthpiece arrangement act as a pressure controlled valve, which transmits energy into the instrument for the initialisation and maintenance of oscillations in the acoustic resonator. The reed can be modelled as a damped nonlinear oscillator so that the motion of a second-order mass-spring system is given by:

$$m_r\left[\frac{d^2x}{dt^2} + \mu\omega_r\frac{dx}{dt} + \omega_r^2(x - x_0)\right] = g(p_\Delta(t), U(t)) \qquad (1)$$

where m_r is the equivalent reed mass, μ is the damping factor, ω_r is fundamental reed frequency, $p_\Delta(t)$ is the difference between the player's oral cavity and the pressure in the reed channel $p_\Delta = (p_{oc} - p_r)$ and $U(t)$ is the steady volume flow through the reed and $g(\cdot)$ is a hard nonlinear function [5, 6]. The reed excitation mechanism (1) is a nonlinear system with memory and estimation of its parameters can be very difficult. In our approach, to define a more general nonlinear model we use neural networks with FIR-IIR synapses and activation functions implemented through an adaptive CR-spline interpolated curve. The parameters that we optimise [2] are the weights of the filter and the control point of the CR-spline activation curve.

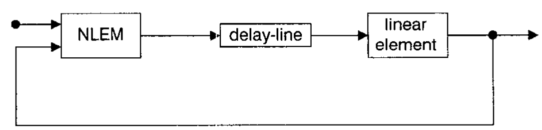

Fig. 1 *Simplified physical model*

The flexible activation function greatly reduces the number of neurons and connections to approximate the NLEM, as it gives an increased expressive power to each neuron. The synthesis network (here called 'adaptive spline recurrent network' (ASRN)) constructed on the basis of the previously described physical model of a single reed instrument is shown in Fig. 2. Once the parameters are fixed with the learning algorithm, the instrument works as a typical physical model instrument.

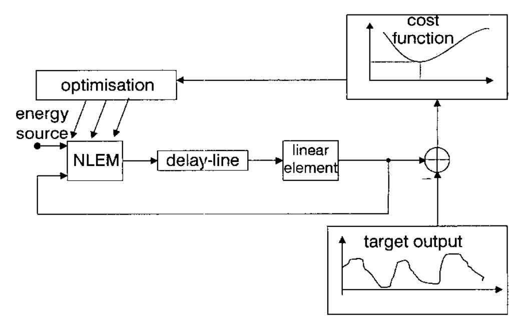

Fig. 2 *Proposed learning based pseudo-physical model*

To obtain a computationally efficient synthesiser, the ASRN makes use of IIR-FIR synapse with power-of-two (or a sum of power-of-two) coefficients. This represents a great advantage in the case of hardware realisation: multipliers can be built using a few simple and fast shift registers instead of slower floating-point arithmetic, and such a strategy can reduce both VLSI silicon area and computational time. Moreover, as specified in [2], the activation function can be easily efficiently implemented both in hardware and software or after learning, simply realised through a lookup table.

ASRN learning by Tabu Search: Several batch or on-line algorithms to train locally recurrent neural networks have been developed [3].