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Application of adaptive simulated annealing to blind channel identification with HOC fitting

S. Chen, B.L. Luk and Y. Liu

A higher order cumulant (HOC) fitting approach is a powerful technique for blind identification of nonminimum phase channels. Owing to the fact that HOC cost functions are multimodal, global optimisation techniques offer the important advantage of avoiding local minima. An adaptive simulated annealing (ASA) algorithm is applied to optimise an HOC cost function. A simulation study demonstrates that this ASA is accurate and has a fast convergence rate compared with standard simulated annealing (SA).

Introduction: An important class of blind identification techniques for nonminimum phase channels is based on the higher order cumulant (HOC) fitting method [1, 2]. HOC cost functions are, however, multimodal, and conventional gradient methods [3, 4] may converge to give 'wrong' solutions. To overcome the problem of local minima, a simulated annealing (SA) algorithm has been applied to optimise an HOC cost function [5]. Although SA represents a general global optimisation technique, it suffers from the serious drawback of being too slow. An improved version of SA, known as adaptive simulated annealing (ASA) [6, 7], provides a significant improvement in convergence speed. We use this ASA algorithm for blind channel identification. Simulation results confirm that this ASA achieves faster convergence in the HOC fitting process.

We will assume a real-valued channel and a PAM symbol constellation. The channel is modelled as a finite impulse response filter with an additive white Gaussian noise:

$$r(k) = \sum_{i=0}^{n_a} a_i s(k-i) + e(k) \qquad (1)$$

Blind identification refers to the determination of the channel $\mathbf{a} = [a_0\ a_1\ \cdots\ a_{n_a}]^T$ using only the noisy received signal $\{r(k)\}$ and some knowledge of the statistical properties of $s(k)$.

Method: In HOC fitting, the channel model is obtained by optimising an HOC cost function. The fourth-order cumulant cost function adopted in our application is defined by

$$J(\hat{\mathbf{a}}) = \sum_{\tau=-\hat{n}_a}^{\hat{n}_a} \left(\hat{C}_{4,r}(\tau,\tau,\tau) - \gamma_{4,s} \sum_{i=\max\{0,-\tau\}}^{\min\{\hat{n}_a,\hat{n}_a-\tau\}} \hat{a}_i \hat{a}_{i+\tau}^3 \right)^2 \qquad (2)$$

where $\hat{C}_{4,r}(\tau, \tau, \tau)$ is the time estimate of the diagonal slice of the fourth-order cumulant for $r(k)$, $\gamma_{4,s}$ is the kurtosis of $s(k)$, $\hat{n}_a$ is an estimated channel length, and $\hat{\mathbf{a}}$ is the channel estimate.

HOC cost functions are well known as being multimodal, and gradient optimisation methods may fail to work. Using a global optimisation method, such as SA, has the advantage of guaranteeing that a global optimal channel estimate will be found. Global optimisation algorithms however, usually, suffer from the drawbacks of slow convergence and high computational cost. ASA [6, 7] is a very fast version of SA. We apply ASA to optimise the cost function (eqn. 2). A flow chart of the algorithm is depicted in Fig. 1.

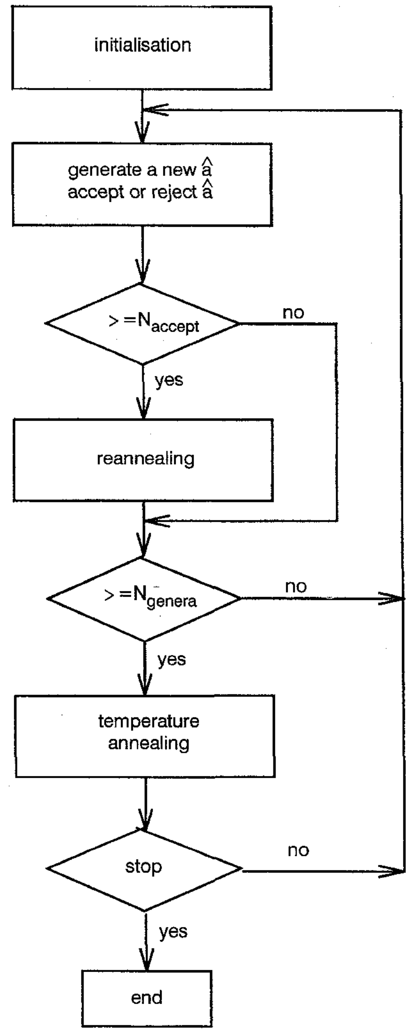

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Fig. 1 *Flow chart of adaptive simulated annealing*

In the initialisation, an initial $\hat{\mathbf{a}}$ is randomly generated; the temperature of the acceptance probability function T_c is set to the initial value of the cost function, and the temperatures of the parameter generating probability functions, T_i, $0 \le i \le \hat{n}_a$, are set to 1.0. Two control parameters in annealing, the coefficient c and the quenching factor Q, are also given, and the annealing times, k_i for $0 \le i \le \hat{n}_a$ and k_c, are all set to 0.

The algorithm generates a new point in the parameter space with:

$$\hat{a}_i^{new} = \hat{a}_i^{old} + y_i(B_i - A_i) \quad \text{and} \quad \hat{a}_i^{new} \in [A-i, B-i] \quad \text{for } 0 \le i \le \hat{n}_a \qquad (3)$$

where A_i and B_i are the lower and upper bounds for a_i, respectively; y_i is calculated as

$$y_i = \mathrm{sgn}\left(u_i - \frac{1}{2}\right) T_i \left(\left(1 + \frac{1}{T_i}\right)^{|2u_i - 1|} - 1 \right) \qquad (4)$$

and u_i is a uniformly distributed random variable in [0, 1]. The new point $\hat{\mathbf{a}}^{new}$ is accepted or rejected according to the acceptance probability function

$$P_{accept} = \frac{1}{1 + \exp((J(\hat{\mathbf{a}}^{new}) - J(\hat{\mathbf{a}}^{old}))/T_c)} \qquad (5)$$

After every N_{accept} acceptance point, the algorithm performs reannealing by rescaling k_i according to the sensitivity $\partial J/\partial a_i$ and resetting k_c to the current optimal value of the cost function (see [6, 7] for details). The derivatives $\partial J/\partial a_i$ are actually calculated using the first-order difference approximations. After every N_{genera} generated points, annealing takes place with $k_i = k_i + 1$ for $0 \le i \le \hat{n}_a$ and $k_c = k_c + 1$:

$$T_i(k_i) = T_i(0)\exp\left(-ck_i^{Q/(1+\hat{n}_a)}\right) \qquad 0 \le i \le \hat{n}_a \quad (6)$$

and

$$T_c(k_c) = T_c(0)\exp\left(-c_k^{Q/(1+\hat{n}_a)}\right) \quad (7)$$

The algorithm is terminated if either the parameters have remained unchanged for a few successive reannealings, or a preset maximum number of function evaluations has been reached.

Table 1: Blind identification results averaged over 100 runs

	True	Estimate (mean ± standard deviation)
	$n_a = 4$	$\hat{n}_a = 5$
a_0	–0.21	–0.2090 ± 0.0441
a_1	–0.50	–0.5042 ± 0.0305
a_2	0.72	0.7186 ± 0.0164
a_3	0.36	0.3708 ± 0.0441
a_4	0.21	0.2119 ± 0.0409
a_5	—	–0.0084 ± 0.0574

Results: The above ASA algorithm was used in the blind identification of the following channel

$$\mathbf{a} = [-0.21 \ -0.50 \ 0.72 \ 0.36 \ 0.21]^T \quad (8)$$

with 8-PAM data symbols and a signal-to-noise ratio of 20dB. In practice, the true channel length $n_a = 4$ is unknown and, therefore, an estimated $\hat{n}_a = 5$ was assumed in simulation. Figs. 2 and 3 show the evolutions of the cost function and the mean tap error (MTE), defined as MTE = $\|\hat{\mathbf{a}} - \mathbf{a}\|^2$, averaged over 10 different runs, respectively. Table 1 summarises the blind identification results. It can be seen that ASA achieved convergence after 8000 function evaluations. The conventional SA employed in [5] required > 20000 function evaluations.

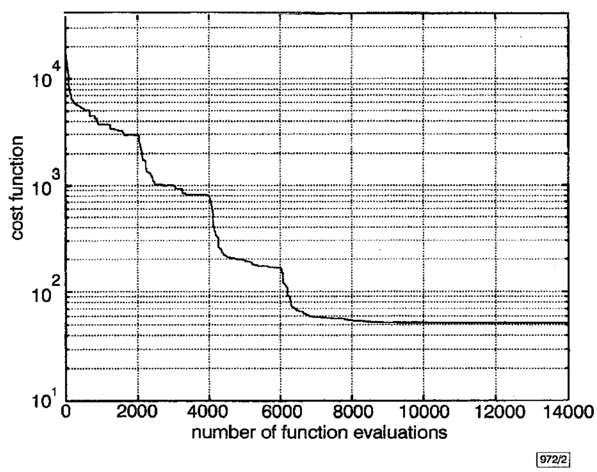

Fig. 2 *Cost function against number of function evaluations averaged over 10 runs*

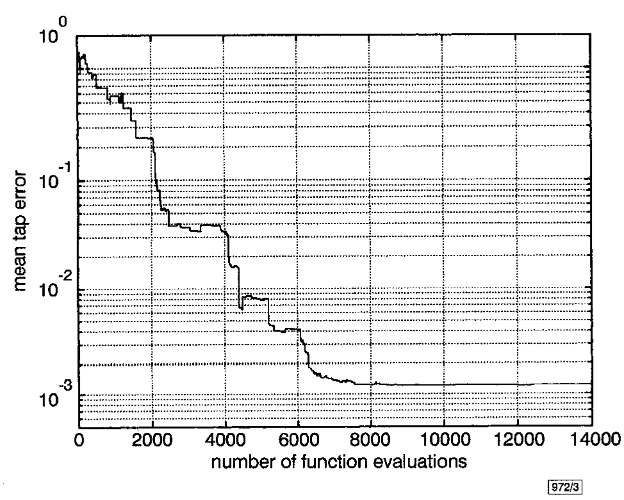

Fig. 3 *Mean tap error against number of function evaluations averaged over 10 runs*

Conclusions: An ASA algorithm has been implemented for blind identification of nonminimum phase channels based on the HOC fitting approach. ASA is a global optimisation method that is considerably faster than standard versions of SA. Our simulation study has confirmed that ASA offers a viable global optimisation tool for obtaining an accurate channel estimate using only noisy received signals.

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Chaotic sequences for multiple access

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The use of chaotic signals as generators of binary and multilevel sequences suitable for code division multiple access (CDMA) is proposed. The number of obtained sequences is found to be greater than the number of *m*-sequences of the same length. These new chaotic sequences are used as spreading codes in a CDMA system. Simulation results are presented and compared with those obtained for *m*-sequences in terms of BER performance.

Introduction: Chaotic signals have been proposed in communications systems in different contexts. In some systems, the synchronisation properties of some chaotic systems have been used in an additive form in order to hide information [1]. Other works propose the use of chaos for spread spectrum [2, 3] using time discrete chaotic maps, which produce continuous range sequences. In this Letter, binary and four-level chaotic sequences suitable for multiple access are proposed.

Since the performance of a code division multiple access (CDMA) system depends, among other parameters, on the spreading properties of the code sequences, in order to guarantee an adequate performance, the proposed digital chaotic sequences are selected as satisfying a suitable correlation criterion.

Chaotic signals: The generation of orthogonal sequences is of utmost importance in multi-code CDMA systems, in order to increase the spectrum efficiency in multirate communications systems [4]. In CDMA, sets of non-correlated sequences with good autocorrelation and crosscorrelation properties are required in order to provide low interference between users [5]. It is also known that traditionally used *m*-sequences exhibit a poor crosscorrelation performance. However, the noise-like performance of the chaotic solutions allows us to obtain sequences with desirable properties for CDMA.