Blind Joint Maximum Likelihood Channel Estimation and Data Detection for Single-Input Multiple-Output Systems

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Abstract— **A blind adaptive scheme is proposed for joint maximum likelihood (ML) channel estimation and data detection of single-input multiple-output (SIMO) systems. The joint ML optimization of the channel and data estimation is decomposed into an iterative optimization loop. An efficient global optimization algorithm termed as the repeated weighted boosting aided search is employed first to identify the unknown SIMO channel model, and then the Viterbi algorithm is used for the maximum likelihood sequence estimation of the unknown data sequence. A simulation example is used for demonstrating the efficiency of this joint ML optimization scheme designed for blind adaptive SIMO systems.**

I. Introduction

The single-input multiple-output (SIMO) system consisting of a single-antenna transmitter and a receiver equipped with multiple antennas has enjoyed popularity owing to its simplicity. A space-time equalizer (STE) based on this SIMO structure is capable of mitigating the channel impairments arising from hostile multipath propagation. For the sake of improving the achievable system throughput, employing blind adaptation of the STE is attractive, since this avoids the reduction of the effective throughput by invoking training. Blind space-time equalization of the SIMO system can be performed by directly adjusting the STE's parameters using a constant modulus algorithm (CMA) type adaptive scheme [1]-[3]. The attainable blind space-time equalization performance can be further improved upon aiding the CMA by a soft decision-directed scheme [4]. The research of blind adaptive SIMO systems has also been focused on blind channel identification [5]-[7]. Once the SIMO channel impulse responses (CIRs) have been identified, various designs, such as the minimum mean square error or minimum bit error rate requires [8] can be invoked for the STE. Alternatively, the decoupled weighted iterative least squares with projection (DW-ILSP) algorithm [9],[10] can be adopted. The DW-ILSP algorithm is a batch EM-type algorithm, which iteratively performs channel estimation and symbol detection.

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This paper develops a blind adaptive joint maximum likelihood (ML) channel estimation and data detection scheme for the SIMO system considered. The proposed algorithm decomposes the joint optimization of the channel and data estimation into an iterative optimization loop by combining a global optimization method, referred to as the repeated weighted boosting search technique (RWBS) [11] invoked for the optimal estimation of the SIMO channel and the Viterbi algorithm (VA) for the maximum likelihood sequence estimation of the transmitted data sequence. Specifically, first, the RWBS algorithm [11] searches the channel parameter space to optimize the ML criterion. Then the VA decodes the data based on the given channel model and feeds back the corresponding likelihood metric to the RWBS algorithm. The efficiency of this joint ML estimation scheme invoked for blind equalization of the SIMO system is demonstrated by a simulation example. We point out that a genetic algorithm (GA) can be used instead of the RWBS algorithm to optimize the SIMO channel estimate. In this case the proposed scheme becomes an extension of the joint ML channel and data estimation scheme using the GA originally developed for the single-input single-output (SISO) system [12].

II. The proposed blind joint ML estimation algorithm

Consider the SIMO system employing a single transmitter antenna and L (> 1) receiver antennas. The symbol-rate sampled antennas' outputs $x_l(k)$, $1 \leq l \leq L$, are given by

$$x_l(k) = \sum_{i=0}^{n_c-1} c_{i,l} s(k-i) + n_l(k) \tag{1}$$

where $n_l(k)$ is the complex-valued Gaussian white noise associated with the lth channel and $E[|n_l(k)|^2] = 2\sigma_n^2$, $\{s(k)\}$ is the transmitted symbol sequence and is assumed to take values from the quadrature phase shift keying (QPSK) symbol set $\{\pm \pm j\}$, while $c_{i,l}$ are the

TABLE I

THE SIMULATED SIMO SYSTEM.

l	Channel impulse response		
1	0.365-0.274j	0.730+0.183j	-0.440+0.176j
2	0.278+0.238j	-0.636+0.104j	0.667-0.074j
3	-0.639+0.249j	-0.517-0.308j	0.365+0.183j
4	-0.154+0.693j	-0.539-0.077j	0.268-0.358j

CIR taps associated with the lth receive antenna. For notational simplicity, we have assumed that each of the L channels has the same length of n_c. Let

$$\begin{aligned} \mathbf{x} &= [x_1(1)\ x_1(2) \cdots x_1(N)\ x_2(1) \cdots \\ &\quad x_L(1)\ x_L(2) \cdots x_L(N)]^T \quad (2) \\ \mathbf{s} &= [s(-n_c+2) \cdots s(0)\ s(1) \cdots s(N)]^T \quad (3) \\ \mathbf{c} &= [c_{0,1}\ c_{1,1} \cdots c_{n_c-1,1}\ c_{0,2} \cdots \\ &\quad c_{0,L}\ c_{1,L} \cdots c_{n_c-1,L}]^T \quad (4) \end{aligned}$$

be the vector of $(N \times L)$ received signal samples, the corresponding transmitted data sequence and the vector of the SIMO CIRs, respectively. The probability density function of the received data vector $\mathbf{x}$ conditioned on the SIMO CIR $\mathbf{c}$ and the symbol vector $\mathbf{s}$ is

$$p(\mathbf{x}|\mathbf{c},\mathbf{s}) = \frac{1}{(2\pi\sigma_n^2)^{NL}} e^{-\frac{1}{2\sigma_n^2}\sum_{k=1}^{N}\sum_{l=1}^{L}\left|x_l(k)-\sum_{i=0}^{n_c-1} c_{i,l}s(k-i)\right|^2} \quad (5)$$

The joint ML estimate of $\mathbf{c}$ and $\mathbf{s}$ is obtained by jointly maximizing $p(\mathbf{x}|\mathbf{c},\mathbf{s})$ over $\mathbf{c}$ and $\mathbf{s}$. Equivalently, the joint ML estimate is the minimum of the cost function

$$J_{\mathrm{ML}}(\hat{\mathbf{c}},\hat{\mathbf{s}}) = \frac{1}{N}\sum_{k=1}^{N}\sum_{l=1}^{L}\left|x_l(k) - \sum_{i=0}^{n_c-1} \hat{c}_{i,l}\hat{s}(k-i)\right|^2 \quad (6)$$

namely

$$(\hat{\mathbf{c}}^*,\hat{\mathbf{s}}^*) = \arg\left[\min_{\hat{\mathbf{c}},\hat{\mathbf{s}}} J_{\mathrm{ML}}(\hat{\mathbf{c}},\hat{\mathbf{s}})\right]. \quad (7)$$

The joint minimization process (7) can also be solved using an iterative loop first over the data sequences $\hat{\mathbf{s}}$ and then over all the possible channels $\hat{\mathbf{c}}$:

$$(\hat{\mathbf{c}}^*,\hat{\mathbf{s}}^*) = \arg\left[\min_{\hat{\mathbf{c}}}\left(\min_{\hat{\mathbf{s}}} J_{\mathrm{ML}}(\hat{\mathbf{c}},\hat{\mathbf{s}})\right)\right]. \quad (8)$$

The inner or lower-level optimization can readily be carried out using the standard VA. In order to guarantee a joint ML estimate, the search algorithm used in the outer or upper-level optimization should be capable of efficiently identifying the globally optimal or near-optimal channel estimate. We employ the RWBS guided random search algorithm [11] to perform the outer optimization task. The detailed RWBS algorithm is given in the Appendix. The proposed blind joint ML optimization scheme can now be summarized.

Outer level Optimization. The RWBS algorithm searches the SIMO channel parameter space to find the globally optimal estimate $\hat{\mathbf{c}}^*$ by minimizing the mean square error (MSE)

$$J_{\mathrm{MSE}}(\hat{\mathbf{c}}) = J_{\mathrm{ML}}(\hat{\mathbf{c}},\tilde{\mathbf{s}}^*). \quad (9)$$

Inner level optimization. Given the channel estimate $\hat{\mathbf{c}}$, the VA provides the ML decoded data sequence $\tilde{\mathbf{s}}^*$, and feeds back the corresponding value of the likelihood metric $J_{\mathrm{ML}}(\hat{\mathbf{c}},\tilde{\mathbf{s}}^*)$ to the upper level.

Let C_{VA} be the complexity of the VA required to decode a data sequence of $(N \times L)$ samples, and denote the total number of VA calls required for the RWBS algorithm to converge by N_{VA}. The complexity of the proposed scheme may be estimated as $(N_{\mathrm{VA}} \times C_{\mathrm{VA}})$. The RWBS algorithm is a simple yet efficient global search algorithm. In several global optimization applications investigated in [11], including the blind joint ML channel estimation and data detection in the context of the SISO system, the RWBS algorithm achieved a similar convergence speed as the GA and was seen to be more accurate after convergence to its minimum than the GA. The RWBS algorithm has additional advantages of requiring a minimum programming effort and having a ?? number of algorithmic parameters that have to be set.

III. SIMULATION EXAMPLE

The number of receive antennas was $L = 4$, in our simulations while, the transmitted data symbols were QPSK modulated, and the SIMO CIRs listed in Table I were used. The length of data samples was $N = 50$. In practice, the value of the likelihood metric $J_{\mathrm{MSE}}(\hat{\mathbf{c}})$ is all that the upper level optimizer has access to, and the convergence of the algorithm can only be quantified in terms of the MSE (9). The performance of the algorithm may also be assessed in terms of the mean tap error defined as

$$\mathrm{MTE} = \|\mathbf{c} - a \cdot \hat{\mathbf{c}}\|^2 \quad (10)$$

where

$$a = \begin{cases} +1, & \text{if } \hat{\mathbf{c}} \to +\mathbf{c} \\ -1, & \text{if } \hat{\mathbf{c}} \to -\mathbf{c} \\ -j, & \text{if } \hat{\mathbf{c}} \to +j\mathbf{c} \\ +j, & \text{if } \hat{\mathbf{c}} \to -j\mathbf{c}. \end{cases} \quad (11)$$

Note that since $(\hat{\mathbf{c}}^*,\hat{\mathbf{s}}^*)$, $(-\hat{\mathbf{c}}^*,-\hat{\mathbf{s}}^*)$, $(-j\hat{\mathbf{c}}^*,+j\hat{\mathbf{s}}^*)$ and $(+j\hat{\mathbf{c}}^*,-j\hat{\mathbf{s}}^*)$ are all legitimate solutions of the joint

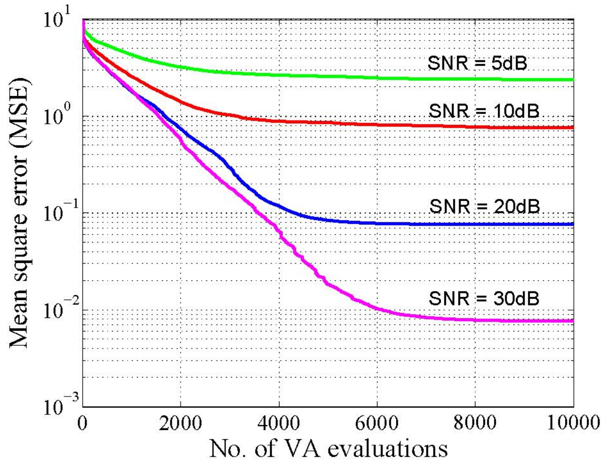

Fig. 1. Mean square error against the number of VA evaluations averaged over 50 simulation runs using the RWBS algorithm for the SIMO channel listed in Table I. The length of the data samples is $N = 50$.

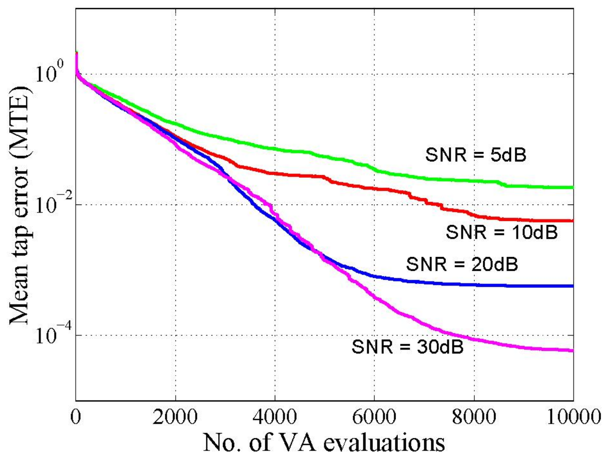

Fig. 2. Mean tap error against the number of VA evaluations averaged over 50 simulation runs using the RWBS algorithm for the SIMO channel listed in Table I. The length of the data samples is $N = 50$.

ML estimation problem (7), the channel estimate $\hat{\mathbf{c}}$ may converge to $\mathbf{c}$, $-\mathbf{c}$, $j\mathbf{c}$ or $-j\mathbf{c}$.

Figs. 1 and 2 show the evolution of the MSE and MTE averaged over 50 simulation runs and for different values of signal to noise ratio (SNR), respectively, obtained by the proposed blind joint ML optimization scheme using the RWBS. It can be seen from Fig. 1, that the MSE converged to the noise floor. The phase ambiguity of 90°, 180° or 270° associated with the blind ML estimate of s cannot be resolved by the blind adaptive scheme itself. In practice, this ambiguity is resolved either by adopting differential encoding or by employing a few pilot training symbols. We assist the blind adaptive scheme by using differential encoding.

Fig. 3 depicts the bit error ratio (BER) of the blind joint ML optimization scheme using differential encoding, in comparison to the BERs of the optimal maximum likelihood sequence estimator in the perfectly known channel scenario both with and without differential encoding. It is seen that the proposed blind scheme only induced by less than 1dB degradation in SNR terms compared to the perfect channel scenario using differential encoding. We also investigated using an appropriately constituted GA to perform the upper-level optimization, and the results obtained by this GA-based blind joint ML estimation scheme are presented in Figs. 4 and 5. By comparing Fig. 1 with Fig. 4, it can be seen that both the RWBS and GA based schemes have a similar convergence speed in terms of the total number of VA evaluations required. It can also be seen that the true estimation accuracy of the RWBS-based scheme is better than that of the GA-based one, as confirmed by comparing Fig. 2 and Fig. 5.

IV. Conclusions

A global optimization method referred to as the RWBS algorithm, has been developed for blind space-time equalization of SIMO systems based on joint ML channel estimation and data detection. The proposed algorithm provides the best performance in comparison to a range of other blind adaptive schemes designed for SIMO systems, at the expense of a higher computational complexity. Our simulation study has shown that this blind joint ML optimization scheme requires a low number of received data samples to approach the maximum likelihood sequence estimation scheme's

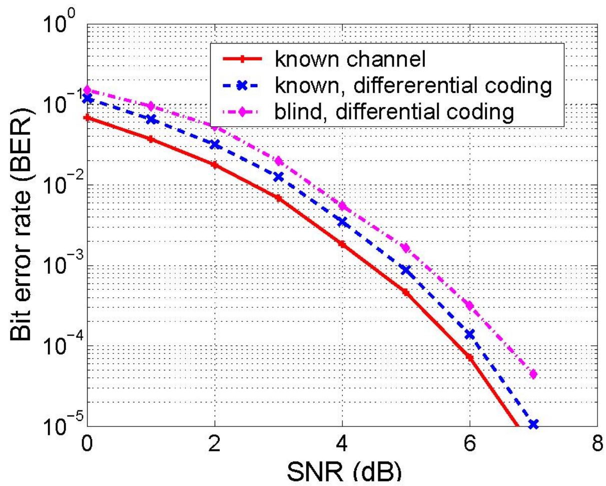

Fig. 3. Comparison of bit error rate performance using the maximum likelihood sequence detection for the SIMO channel listed in Table I. The length of data samples for the blind scheme is $N = 50$.

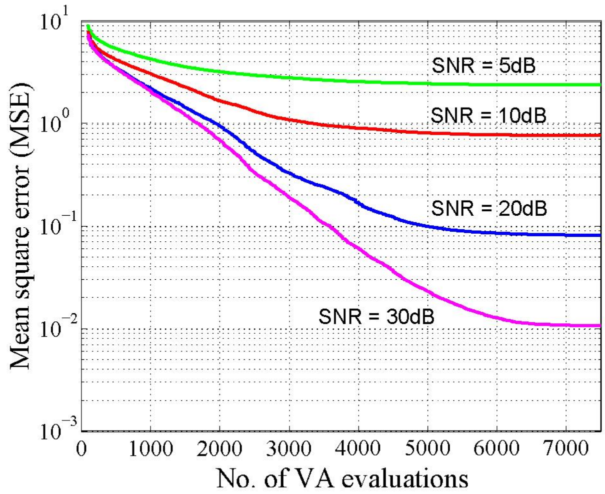

Fig. 4. Mean square error against number of VA evaluations averaged over 50 runs using the GA for the SIMO channel listed in Table I. The length of data samples $N = 50$.

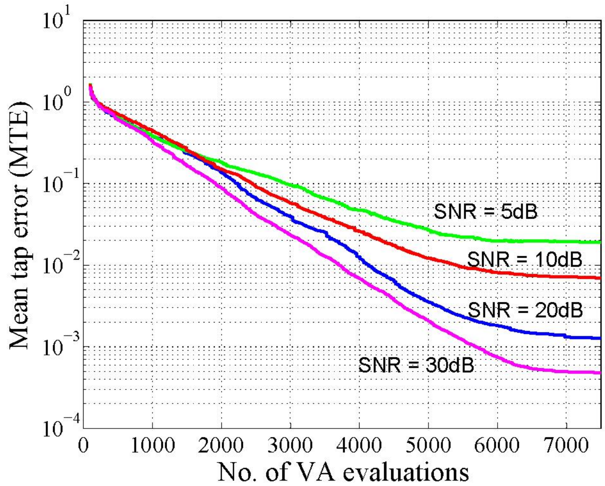

Fig. 5. Mean tap error against the number of VA evaluations averaged over 50 simulation runs using the GA for the SIMO channel listed in Table I. The length of data samples is $N = 50$.

performance.

APPENDIX. REPEATED WEIGHTED BOOSTING SEARCH

Consider solving the generic optimization problem

$$\min_{\mathbf{u}\in\mathcal{U}} J(\mathbf{u}), \tag{12}$$

where $\mathcal{U}$ defines the feasible set of $\mathbf{u}$, using the RWBS algorithm of [11]. The algorithm is detailed below.

Specify the following algorithmic parameters: P_S – population size, N_G – number of generations in the repeated search, N_B – number of iterations in the weighted boosting search and ξ_B – accuracy required for terminating the weighted boosting search.

Outer loop: generations For $g = 1 : N_G$

Generation initialization: Initialize the population by setting $\mathbf{u}_1^{(g)} = \mathbf{u}_{\text{best}}^{(g-1)}$ and randomly generating the rest of the population members $\mathbf{u}_i^{(g)}$, $2 \le i \le P_S$, where $\mathbf{u}_{\text{best}}^{(g-1)}$ denotes the solution found in the previous generation. If $g = 1$, $\mathbf{u}_1^{(g)}$ is also randomly chosen.

Weighted boosting search initialization: Assign the initial distribution weight $\delta_i(0) = \frac{1}{P_S}$, $1 \le i \le P_S$, for the population, and calculate the cost function value of each point according to

$$J_i = J(\mathbf{u}_i^{(g)}),\ 1 \le i \le P_S$$

.

Inner loop: weighted boosting search For $t = 1 : N_B$

Step 1: Boosting

1) Find

$$i_{\text{best}} = \arg \min_{1\le i\le P_S} J_i$$

and

$$i_{\text{worst}} = \arg \max_{1\le i\le P_S} J_i$$

Denote $\mathbf{u}_{\text{best}}^{(g)} = \mathbf{u}_{i_{\text{best}}}^{(g)}$ and $\mathbf{u}_{\text{worst}}^{(g)} = \mathbf{u}_{i_{\text{worst}}}^{(g)}$.

2) Normalize the cost function values

$$\bar{J}_i = \frac{J_i}{\sum_{m=1}^{P_S} J_m},\ 1 \le i \le P_S.$$

3) Compute a weighting factor β_t according to

$$\eta_t = \sum_{i=1}^{P_S} \delta_i(t-1)\bar{J}_i,\ \beta_t = \frac{\eta_t}{1-\eta_t}.$$

4) Update the distribution weighting for $1 \le i \le P_S$

$$\delta_i(t) = \begin{cases} \delta_i(t-1)\beta_t^{\bar{J}_i}, & \text{for } \beta_t \le 1 \\ \delta_i(t-1)\beta_t^{1-\bar{J}_i}, & \text{for } \beta_t > 1 \end{cases}$$

and normalize them according to

$$\delta_i(t) = \frac{\delta_i(t)}{\sum_{m=1}^{P_S} \delta_m(t)},\ 1 \le i \le P_S.$$

Step 2: Parameter updating

1) Construct the $(P_S + 1)$th point using the formula

$$\mathbf{u}_{P_S+1} = \sum_{i=1}^{P_S} \delta_i(t)\mathbf{u}_i^{(g)}.$$

2) Construct the $(P_S + 2)$th point using the formula

$$\mathbf{u}_{P_S+2} = \mathbf{u}_{\text{best}}^{(g)} + \left(\mathbf{u}_{\text{best}}^{(g)} - \mathbf{u}_{P_S+1}\right).$$

3) Compute the cost function values $J(\mathbf{u}_{P_S+1})$ and $J(\mathbf{u}_{P_S+2})$ for these two points and find

$$i_* = \arg \min_{i=P_S+1, P_S+2} J(\mathbf{u}_i).$$

4) The pair $(\mathbf{u}_{i_*}, J(\mathbf{u}_{i_*}))$ then replaces $(\mathbf{u}_{\text{worst}}^{(g)}, J_{i_{\text{worst}}})$ in the population.

If $\|\mathbf{u}_{P_S+1} - \mathbf{u}_{P_S+2}\| < \xi_B$, exit **inner loop**;

End of inner loop.

The solution found in the gth generation is $\mathbf{u} = \mathbf{u}_{\text{best}}^{(g)}$.

End of outer loop.

This yields the solution $\mathbf{u} = \mathbf{u}_{\text{best}}^{(N_G)}$.

To guarantee a global optimal solution as well as to achieve a fast convergence, the algorithmic parameters, P_S, N_G, N_B and ξ_B, have to be carefully set. The appropriate values for these algorithmic parameters depends on the dimension of $\mathbf{u}$ and how hard is the objective function to be optimized. Generally, these algorithmic parameters have to be found empirically, just as in any global optimization algorithm. Using the so-called elitist initialization is very useful,since it retains the information obtained by the previous search generation, which otherwise would be lost due to random sampling based initialization. In the inner loop optimization, there is no need for every members of the population to converge to a (local) minimum, and it is sufficient to locate where the minimum lies. Thus, the number of weighted boosting iterations, N_B, can be set to a relatively small integer and the accuracy required for terminating the weighted boosting search, ξ_B, can be set to a relatively large value. This reduces the search efficient, achieving convergence after a small number of the cost function evaluations. It should be noted, although the formal proof is still required, that inconjunction with a sufficiently high number of generations, the algorithm will reach the globally optimal solution.

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