Assigning parameter estimates for *N*-survivor processing

Sungkwon Jo, Jung Suk Joo and Yong Hoon Lee

In an attempt to improve *N*-survivor processing (NSP), which lies between per-survivor processing and tentative decisions, a new algorithm is proposed for assigning parameter estimates to survivors. The proposed algorithm considers the history of the survivors in a trellis diagram by evaluating the distance between the hypothesised input vectors that contain the path history. It will be shown through computer simulation that NSP employing the proposed algorithm can outperform the original version.

Introduction: Recently, an algorithm [1] that can reduce the computational complexity of per-survivor processing (PSP) [2], a powerful technique for sequence detection in uncertain environments, has been introduced. In contrast to PSP, which estimates unknown parameters for each survivor in the trellis path, this algorithm selects the *N* best survivors at each detection step and then estimates parameters only for those *N* survivors, where $1 \le N \le Q$ and Q denotes the number of trellis states. The remaining $Q - N$ survivors are assigned the parameter estimate associated with the best survivor. This algorithm, which will perform what is referred to as *N*-survivor processing (NSP), can efficiently make a compromise between complexity and performance via adjustment of the parameter *N*.

In this Letter, an attempt will be made to improve NSP. In particular, the algorithm for assigning parameter estimates to the $Q - N$ survivors, which are excluded in the selection of the *N* best survivors, is modified. It will be shown through computer simulation that this modified NSP can outperform the original version.

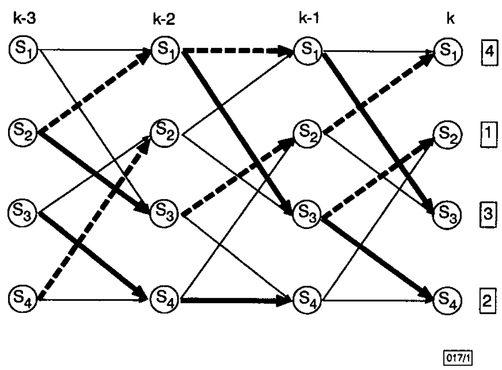

Fig. 1 *Typical trellis evolution events for Q = 4 and N = 2*

States are defined as $\mathbf{s}_1 = (-1, -1)$, $\mathbf{s}_2 = (-1, 1)$, $\mathbf{s}_3 = (1, -1)$, $\mathbf{s}_4 = (1, 1)$
—— survivors
—— binary input 1
- - - - binary input −1

Proposed algorithm: We consider a trellis diagram with Q states for sequence detection. Each state is associated with a survivor, which is a retained trellis path. We let $S = \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_Q\}$ denote the set of states, and $\hat{\mathbf{h}}_k(\mathbf{s}_i)$ be the estimated parameters for the state $\mathbf{s}_i$ at time k. The estimate $\hat{\mathbf{h}}_k(\mathbf{s}_i)$ is obtained under the assumption that the hypothesised input vector associated with the survivor of $\mathbf{s}_i$ at time k is correct. The proposed algorithm is stated as follows: At each time k:

(i) *Step 1:* Select the *N* best survivors with smaller path metric values than the others. Denote the set of these *N* survivors by $S_{k,1}$, and the set associated with the rest by $S_{k,2}$ ($S = S_{k,1} \cup S_{k,2}$).

(ii) *Step 2:* Obtain the parameter estimate $\hat{\mathbf{h}}_k(\mathbf{s}_i)$ for $\mathbf{s}_i \in S_{k,1}$.

(iii) *Step 3:* For each of the survivors associated with the state in $S_{k,2}$, one out of $\{\hat{\mathbf{h}}_k(\mathbf{s}_i) | \mathbf{s}_i \in S_{k,1}\}$ is assigned depending on the distance between the hypothesised input vectors associated with the survivors. Specifically, the estimate $\hat{\mathbf{h}}_k(\mathbf{s}_i)$, for $\mathbf{s}_i \in S_{k,1}$, is assigned to the survivor associated with $\mathbf{s}_j \in S_{k,2}$ if

$$d(\mathbf{x}_{k,i}, \mathbf{x}_{k,j}) = \min_l d(\mathbf{x}_{k,l}, \mathbf{x}_{k,j}) \qquad (1)$$

where $\mathbf{x}_{k,j}$ is the hypothesised input vector for $\mathbf{s}_j$ at time k, $d(\cdot, \cdot)$ is the Euclidean distance, and $\{l\}$ are the indices of the states in $S_{k,1}$.

(iv) *Step 4:* Extend every survivor using its associated parameter estimate.

This algorithm, which will be referred to as the modified NSP, is identical to the original NSP [1] with the exception of step 3: in [1] the parameter estimate corresponding to the best survivor is assigned to all survivors associated with the state $\mathbf{s}_j$ in $S_{k,2}$. A pictorial description of the modified NSP is shown in Fig. 1, in which typical trellis evolution events are shown for $Q = 4$ and $N = 2$. The set of states $S = \{\mathbf{s}_1, \mathbf{s}_2, \mathbf{s}_3, \mathbf{s}_4\} = \{(-1, -1), (-1, 1), (1, -1), (1, 1)\}$; at time k, $S_{k,1} = \{\mathbf{s}_2, \mathbf{s}_4\}$ and $S_{k,2} = \{\mathbf{s}_1, \mathbf{s}_3\}$. The hypothesised input vectors for the survivors at time k are given by $\mathbf{x}_{k,1} = (1\ -1\ -1)$, $\mathbf{x}_{k,2} = (-1\ 1\ -1)$, $\mathbf{x}_{k,3} = (-1\ -1\ 1)$, and $\mathbf{x}_{k,4} = (-1\ 1\ 1)$. Since $\mathbf{x}_{k,1}$ is closer to $\mathbf{x}_{k,2}$ than to $\mathbf{x}_{k,4}$, $\hat{\mathbf{h}}_k(\mathbf{s}_2)$ is assigned to the survivor associated with $\mathbf{s}_1$. In a similar manner, $\hat{\mathbf{h}}_k(\mathbf{s}_4)$ is assigned to the survivor of $\mathbf{s}_3$.

The modified NSP considers the history of the survivors, when assigning parameter estimates, by evaluating the distance between the hypothesised inputs that contain the path history. Owing to this property, the modified NSP has a better performance than the original version that simply assigns the most plausible estimate to all survivors associated with $S_{k,2}$.

Simulation results: To evaluate the performance of the proposed algorithm, computer simulations were performed for the IS-136 TDMA mobile communication systems over Rayleigh fading channels. The modulation scheme was $\pi/4$ DQPSK with a symbol rate of 24.3ksymbol/s. The data sequence was arranged into 162 symbol frames and the first 14 symbols of each frame were designated as a pilot sequence. In the simulation, a total of 3000 frames were generated and transmitted through a two-ray Rayleigh fading channel [3], which was modelled as

$$c(t) = \alpha_0(t)\delta(t) + \alpha_1(t)\delta(t - \tau) \qquad (2)$$

where $\alpha_0(t)$ and $\alpha_1(t)$ are independent zero mean complex Gaussian processes and τ is the time delay between the two rays. For simplicity, a normalised uniform delay power profile was assumed, i.e. $E[|\alpha_0(t)|^2] = E[|\alpha_1(t)|^2] = 0.5$. The parameter τ was assumed to be either $2T$ or $3T$, which leads to maximum likelihood sequence detection (MLSD) with 16 or 64 states. The carrier frequency was 900 MHz and the vehicle speed was 100km/h. The channel parameters were estimated using a recursive least squares (RLS) algorithm with a forgetting factor of 0.65. An MLSD receiver that can employ either the original or modified NSP is illustrated in Fig. 2.

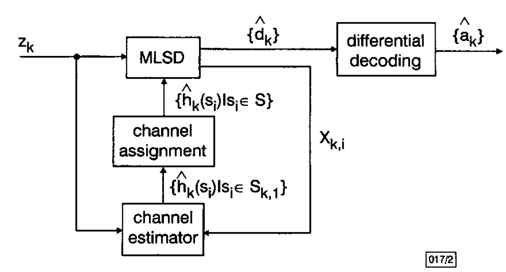

Fig. 2 *MLSD receiver that can employ either original or modified NSP*

z_k is output of receiver filter sampled at $t = kT$ and a_k is transmitted symbol

Assuming perfect timing and carrier recovery, the transmitted $\pi/4$ DQPSK symbols $\{d_k\}$ were coherently detected and differentially decoded to produce estimates of the data symbols $\{a_k\}$. The receiver in Fig. 2 is called either an NSP-MLSD or a modified NSP-MLSD depending on the type of NSP algorithm employed. In one extreme case, when $N = Q$, NSP becomes PSP and the receiver is called a PSP-MLSD. In another extreme case, when $N = 1$, the receiver becomes a tentative decision (TD)-MLSD with a decision delay $d = 0$. In TD-MLSD, the parameters are estimated at each time by using a tentative decision value which is obtained by tracing back the best survivor. The duration of back-tracing is called the decision delay.

Fig. 3 compares the variation of the empirically estimated BER values of the MLSD receivers as N is increased from 1 to Q, while fixing E_b/N_o at 20dB. As expected, both the NSP- and modified NSP-MLSD receivers approached the performance of the PSP-MLSD as N increased; and the latter exhibited a faster convergence. For example, when $Q = 64$, the modified NSP-MLSD converged when $N = 20$ while the NSP-MLSD converged after $N = 40$. The modified NSP required considerably smaller values of N than the original NSP, and the computational saving achieved by the modified NSP was significant. Fig. 4 compares the performances of the TD-, PSP-, NSP- and modified NSP-MLSD receivers as E_b/N_o was varied, while Q was fixed at 16. With the TD-MLSD, several decision delay d values were tried, and the value $d = 2$, which exhibited the best performance, was chosen. The NSP-, modified NSP- and PSP-MLSD considerably outperformed the TD-MLSD. The modified NSP-MLSD with $N = 8$ behaved like the NSP-MLSD with $N = 12$ and was almost comparable to the PSP-MLSD.

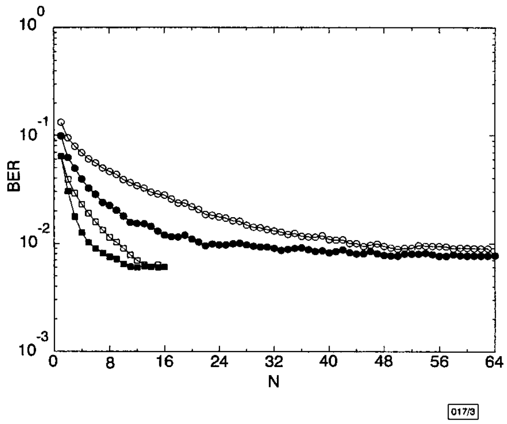

Fig. 3 *Variation of BER performances of MLSD receivers employing NSP- and modified NSP-MLSD as N increases from 1 to Q*

E_b/N_o is fixed at 20 dB and vehicle speed is 100 km/h
□ NSP-MLSD ($Q = 16$)
■ modified NSP-MLSD ($Q = 16$)
○ NSP-MLSD ($Q = 64$)
● modified NSP-MLSD ($Q = 64$)

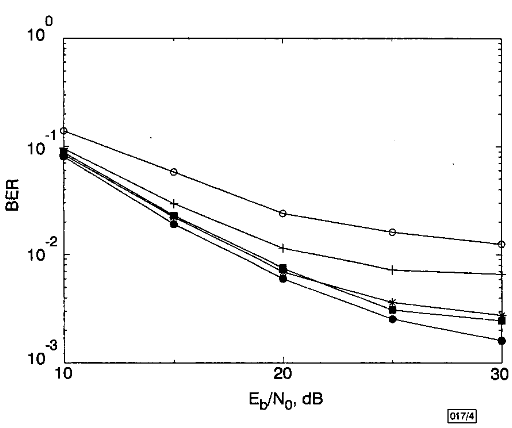

Fig. 4 *Comparison of BER performances*

d is decision delay for TD-MLSD and number of states Q in MLSD is 16
○ TD-MLSD ($d = 2$)
+ NSP-MLSD ($N = 8$)
✳ NSP-MLSD ($N = 12$)
■ modified NSP-MLSD ($N = 8$)
● PSP-MLSD

Conclusion: To improve the performance of the NSP in [1], a new algorithm that considers the history of survivors when assigning parameter estimates was developed. To each survivor excluded in the parameter estimation, the proposed algorithm assigns one of the updated parameter estimates depending on the Euclidean distance between the hypothesised input vectors. Computer simulation results indicate that an NSP-MLSD employing the proposed algorithm outperforms the original NSP-MLSD, and that the computational saving achieved by the proposed algorithm is significant.

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Blind adaptive multiuser detection for DS/CDMA over multipath fading channels

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Using a hard null scheme, multipath fading and multiple access interference suppression can be realised for a multiple constrained minimum variance (MCMV) detector at the same time. A modified version of the MCMV detector is also presented, which utilises the eigenstructure of the correlation matrix to enhance the performance of the MCMV detector. Numerical results demonstrate the effectiveness of the proposed detectors.

Introduction: The constrained minimum output energy (CMOE) criterion has been proposed [1] but it is extremely sensitive to the signal distortion in multipath fading channels. A RAKE receiver exploits multipath diversity but is unable to suppress interference. Although subspace-based blind multiuser detectors can avoid the effect of multipath fading, they suffer from the poor convergence properties of blind channel identification algorithms and cannot employ multiple constraints to null the mismatch of the desired user signal between the nominal signature and the distorted signal [2]. To alleviate the problem of signal suppression, the multiple constrained minimum variance (MCMV) method is realised, based on a choice of constraint matrix, which combines the desired signature waveform and its multipath versions.

Because the multiple constraints increase the output noise power, in this Letter we also propose a method for reducing the effect of the noise component, called the modified MCMV (MMCMV) detector. The computing weight vector of the MMCMV detector involves two steps. In the first step the MCMV detector weight vector is calculated, and in the second step the MCMV detector weight vector is projected onto a signal subspace. The projection operation reduces the norm of the weight vector with the detector responses to the desired signal and interferers remaining unchanged.

Signal model: We consider an asynchronous multiuser DS/CDMA system with K users and a set of normalised signature waveforms $s_k(t)$, $k = 1, 2, ..., K$. T_b and T_c are the common symbol duration and chip interval, repectively, where $T_c = T_b/L$ and $K < L$. We can model the received signal after transmission through a delay channel as

$$x(t) = \sum_{i=-\infty}^{\infty} \sum_{k=1}^{K} \sum_{l=1}^{N_k} \alpha_{k,l} \sqrt{\sigma_k^2} b_k(i) s_{k,l}(t - iT_b - \tau_{k,l}) + n(t) \qquad t \in [-\infty, \infty] \quad (1)$$

where $b_k(i) \in \pm 1$ represents the kth user's information bit during the ith interval, σ_k^2 is the received energy of the kth user's signal and $n(t)$ is white Gaussian noise with variance σ_n^2. N_k, $\tau_{k,l}$ and $\alpha_{k,l}$