

# Estimation and detection from coded signals

Joint research :

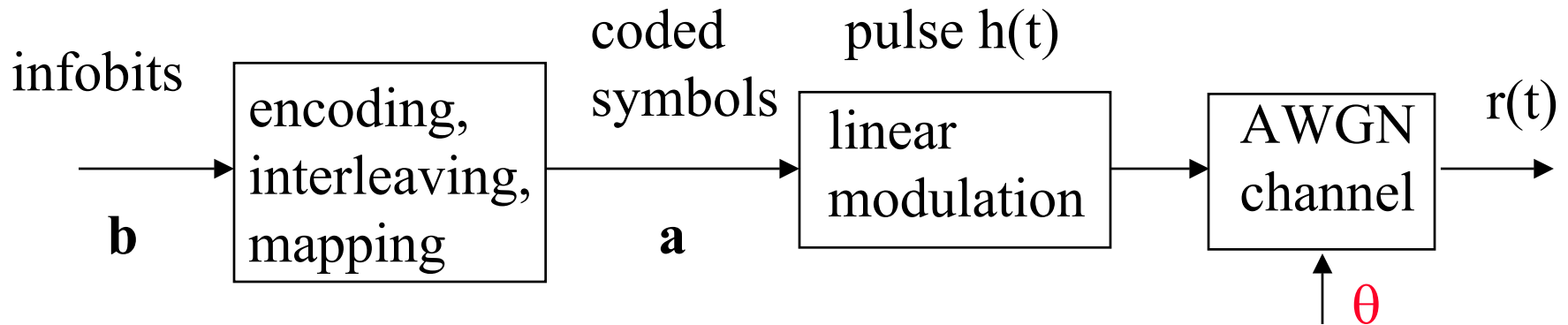
- UGent (N. Noels, H. Wymeersch, H. Steendam, M. Moeneclaey)
- UCL (C. Herzet, L. Vandendorpe)

Presented by Marc Moeneclaey, UGent - TELIN dept.  
Marc.Moeneclaey@telin.UGent.be

## Outline

- Coding + linear modulation,  
AWGN channel, unknown parameter  $\theta$  (carrier phase, ...)
- MAP detection of information bits
  - \*  $\theta$  known
  - \*  $\theta$  unknown
- Low-complexity alternatives to MAP detection for unknown  $\theta$ 
  - \* iterative ML estimation of  $\theta$  (EM algorithm)
  - \* simplified sum-product algorithm
- Numerical results
- Conclusions

## Coding + linear modulation, AWGN channel



$\mathbf{b} \rightarrow \mathbf{a} = \chi(\mathbf{b})$  : turbo code, LDPC code, BICM, ....

$h(t)$  : square-root Nyquist pulse

$\theta$  : unknown parameter (**carrier phase**, time delay, freq. offset, gain)

**received signal** 
$$r(t) = e^{j\theta} \sum_k a_k h(t - kT) + w(t)$$

## MAP detection, $\theta$ known

MAP detection (on individual infobits) achieves minimum BER

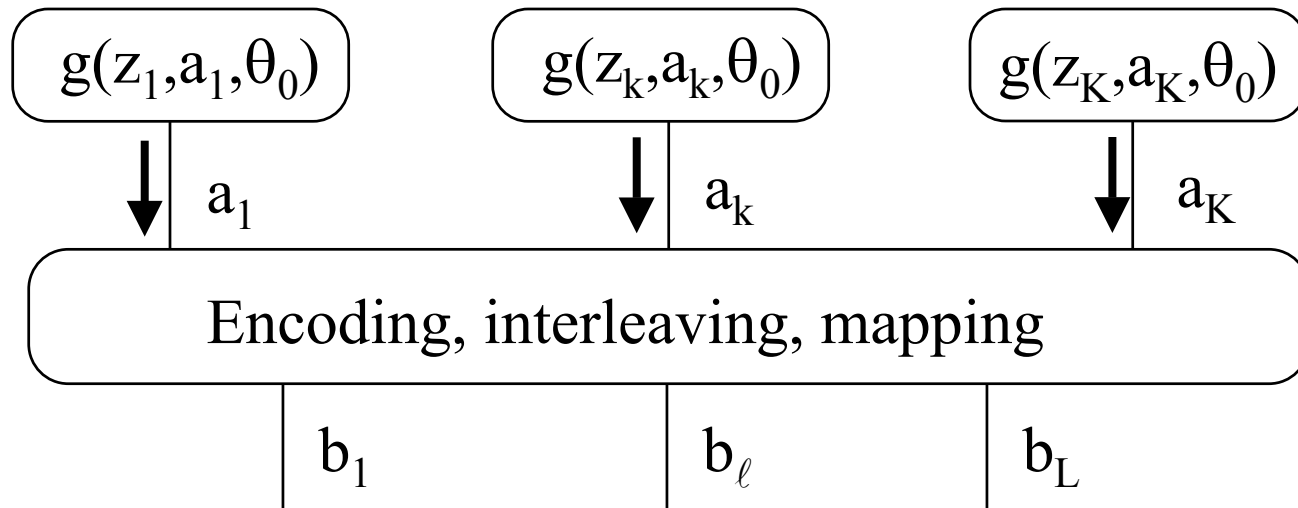
$$\hat{b}_k = \arg \max_{b_k \in \{0,1\}} p(b_k | \mathbf{r}) \quad \mathbf{r} : \text{vector representation of } r(t)$$

Assuming  $\theta = \theta_0$  is known, bit APP  $p(b_k | \mathbf{r})$  is given by

$$p(b_k | \mathbf{r}) \propto \sum_{\mathbf{b}:b_k} p(\mathbf{r} | \mathbf{a} = \chi(\mathbf{b}), \theta_0) \quad (\text{many terms !})$$

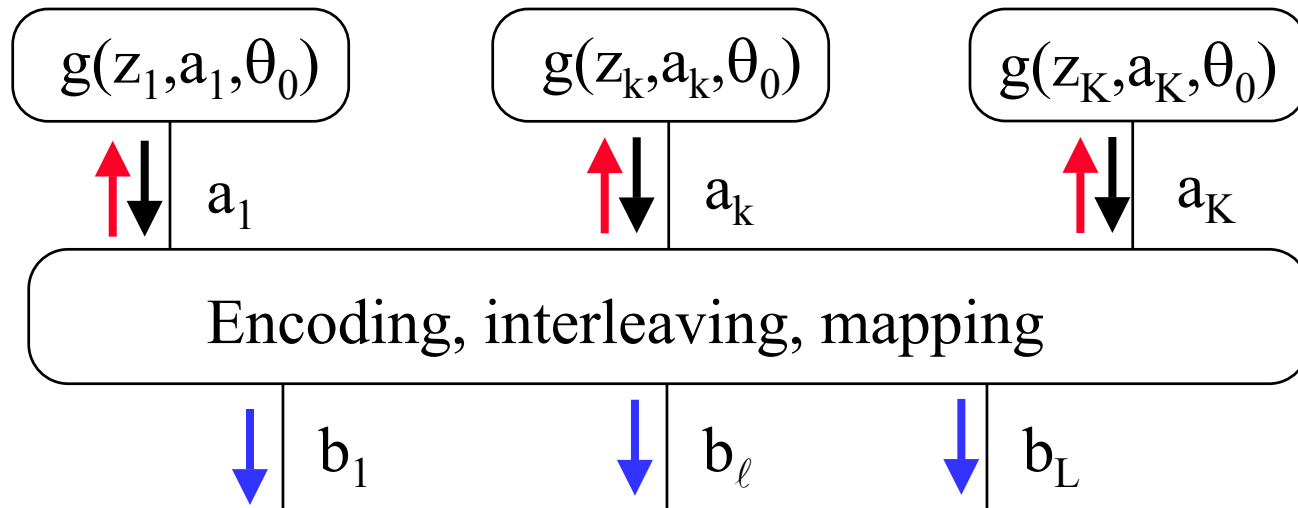
Efficient computation of APPs : *sum-product (SP) algorithm*  
+ *message-passing in factor graph (FG)*)

## Factor graph for known $\theta$



$\downarrow g(z_k, a_k, \theta_0)$  channel observation     
  $g(z_k, a_k, \theta_0) = \exp\left(\frac{2}{N_0} \operatorname{Re}[a_k^* z_k e^{-j\theta}]\right)$

## Factor graph for known $\theta$



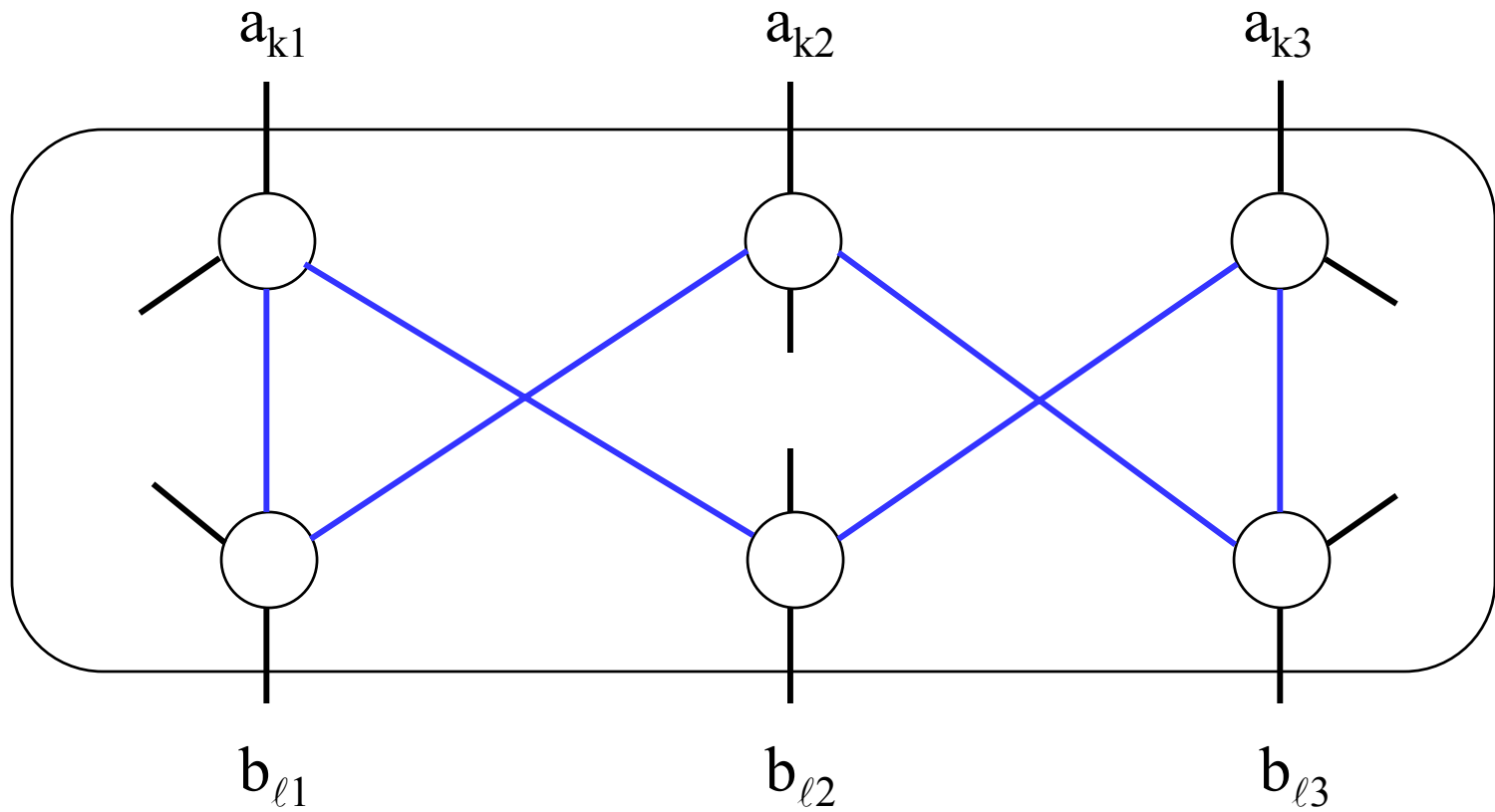
$\downarrow$   $g(z_k, a_k, \theta_0)$  channel observation      $g(z_k, a_k, \theta_0) = \exp\left(\frac{2}{N_0} \operatorname{Re}[a_k^* z_k e^{-j\theta}]\right)$

$\uparrow$   $p_e(a_k)$  extrinsic information on  $a_k$

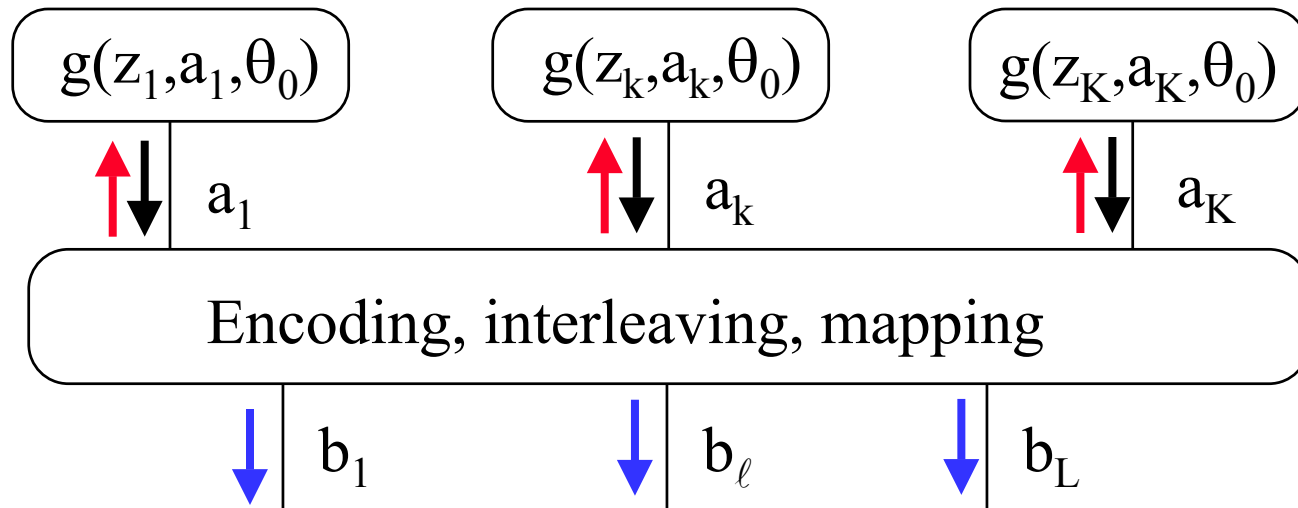
$\downarrow$   $p(b_\ell | \mathbf{r})$  information bit APP

## Factor graph for known $\theta$

Because of **cycles** in FG, MAP detection is *iterative*



## Factor graph, $\theta$ known



$\downarrow$   $g(z_k, a_k, \theta_0)$  channel observation      $g(z_k, a_k, \theta_0) = \exp\left(\frac{2}{N_0} \operatorname{Re}[a_k^* z_k e^{-j\theta}]\right)$

$\uparrow$   $p_e^{(n)}(a_k)$  extrinsic information on  $a_k$

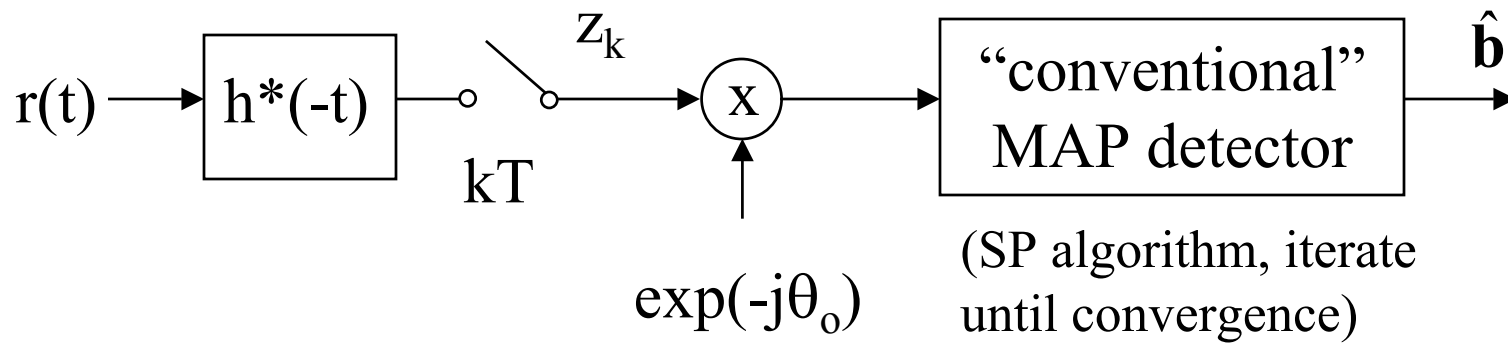
$\downarrow$   $p^{(n)}(b_\ell | \mathbf{r})$  information bit APP

$n$  : iteration index of  
MAP detector

*iterate until convergence*



## Receiver structure, $\theta$ known



## MAP detection, $\theta$ unknown

When  $\theta$  is unknown (uniform distrib.), bit APP is given by

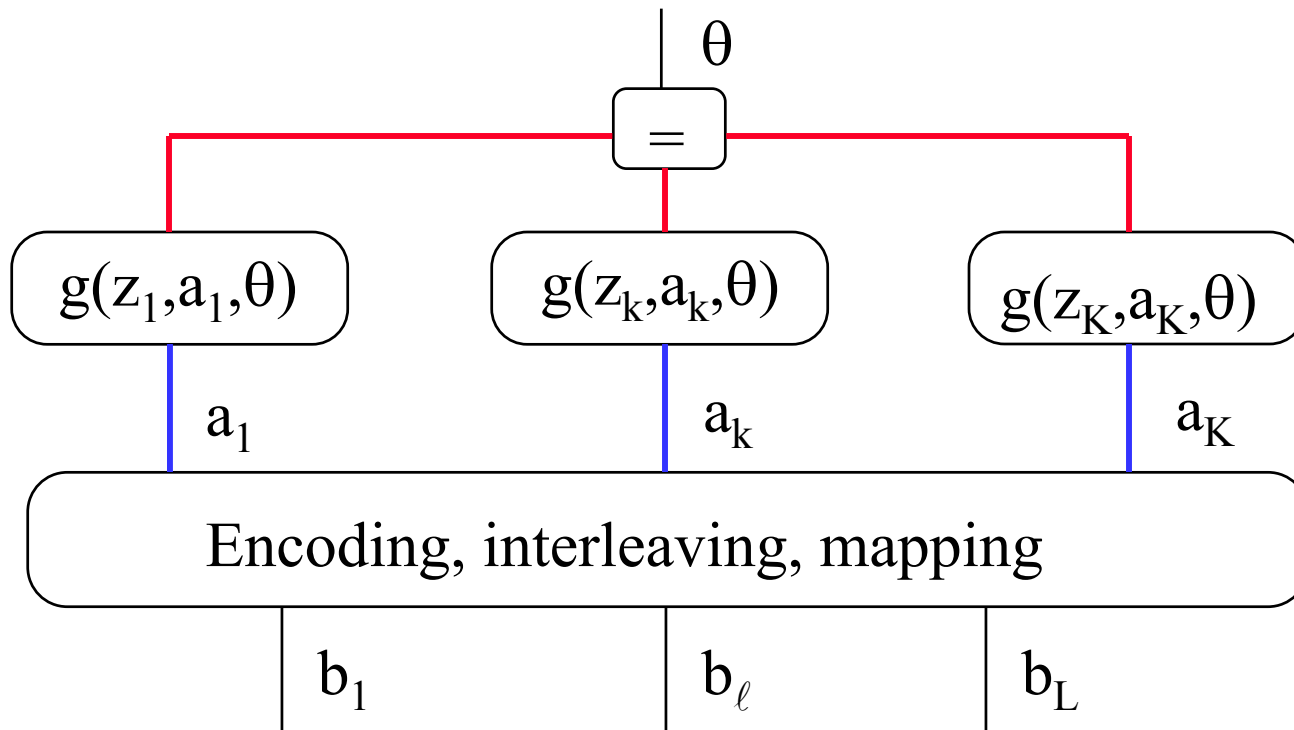
$$p(\mathbf{b}_k | \mathbf{r}) \propto \sum_{\mathbf{b}:\mathbf{b}_k} \left( \int p(\mathbf{r} | \mathbf{a} = \chi(\mathbf{b}), \theta) d\theta \right)$$

≠ conventional MAP detector

hard to compute, because of **integration** over  $\theta$

## Factor graph, $\theta$ unknown

- messages are functions of  $\theta$
- downward messages involve integration over  $\theta$



## Alternatives to exact MAP detection when $\theta$ is unknown

### Alternative 1 : ML parameter estimation

Provide estimate of  $\theta$  to conventional MAP detector

$$\begin{aligned} p(\mathbf{b}_k | \mathbf{r}) &= \int p(\mathbf{b}_k | \mathbf{r}, \theta) p(\theta | \mathbf{r}) d\theta & p(\theta | \mathbf{r}) &\approx \delta(\theta - \hat{\theta}(\mathbf{r})) \\ &\approx p(\mathbf{b}_k | \mathbf{r}, \hat{\theta}(\mathbf{r})) \end{aligned}$$

### Alternative 2 : Simplified sum-product algorithm

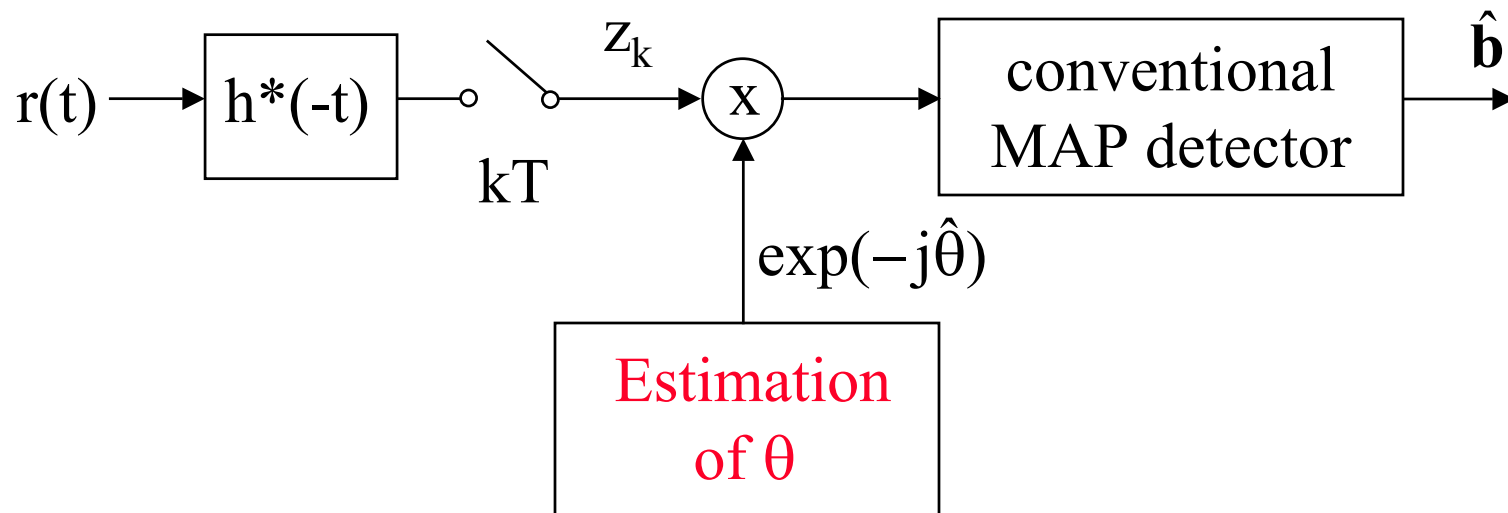
Approximation of  $\theta$ -dependent messages

# **Alternative 1 :**

# **ML parameter estimation**

## Receiver structure when estimating $\theta$

**Strategy** : use conventional MAP detector, but provide *estimate* (instead of correct value) of  $\theta$



## ML parameter estimation

ML estimation of  $\theta$  :  $\hat{\theta}_{\text{ML}} = \arg \max_{\theta} p(\mathbf{r} | \theta)$

For long observation intervals, mean-square error (MSE) of ML estimate converges to **Cramer-Rao lower bound** (CRB) on MSE

Computation of CRB is hard when data symbols are not a priori known to receiver.

Simpler but less tight bound : **modified CRB** (MCRB)  
(assumes data symbols are known to receiver)

## Cramer-Rao bound

$$\text{CRB}^{-1} = E_{\mathbf{r}} \left[ \left( \frac{\partial}{\partial \theta} \ln p(\mathbf{r}; \theta) \right)^2 \right] = -E_{\mathbf{r}} \left[ \frac{\partial^2}{\partial \theta^2} \ln p(\mathbf{r}; \theta) \right]$$

$$p(\mathbf{r}; \theta) = \sum_{\mathbf{a}} p(\mathbf{r} | \mathbf{a}; \theta) p(\mathbf{a}) = E_{\mathbf{a}} [p(\mathbf{r} | \mathbf{a}; \theta)]$$

average over (coded)  
symbol sequence  $\mathbf{a}$   
(*many terms !!*)

analytical difficulty :  $E_{\mathbf{a}}[\cdot]$  “inside”  $\ln(\cdot)$ , so that  $\ln(p(\mathbf{r}; \theta))$  is not a simple function of  $\mathbf{r}$  and  $\theta$



## Modified Cramer-Rao bound

$$\text{MCRB}^{-1} = E_{\mathbf{r}, \mathbf{a}} \left[ \left( \frac{\partial}{\partial \theta} \ln p(\mathbf{r} | \mathbf{a}; \theta) \right)^2 \right] = -E_{\mathbf{r}, \mathbf{a}} \left[ \frac{\partial^2}{\partial \theta^2} \ln p(\mathbf{r} | \mathbf{a}; \theta) \right]$$

$E_{\mathbf{r}, \mathbf{a}}[\cdot]$  “outside”  $\ln(\cdot) \Rightarrow$  MCRB easier to evaluate than CRB,  
when  $\ln(p(\mathbf{r}|\mathbf{a};\theta))$  is simple function of  $\mathbf{a}$  and  $\mathbf{r}$   
(e.g., linear modulation on AWGN channel)

## MCRB for phase estimation

$$\mathbf{r} = \mathbf{a} \exp(j\theta) + \mathbf{w} \quad E[\mathbf{w}\mathbf{w}^T] = \frac{N_0}{2} \mathbf{I}$$

$$\ln p(\mathbf{r} | \mathbf{a}; \theta) = \frac{2}{N_0} \sum_k \operatorname{Re}[a_k^* r_k \exp(-j\theta)]$$

$$\frac{\partial^2}{\partial \theta^2} \ln p(\mathbf{r} | \mathbf{a}; \theta) = \frac{-2}{N_0} \sum_k \operatorname{Re}[a_k^* r_k \exp(-j\theta)]$$

$$\text{MCRB}^{-1} = -E_{\mathbf{r}, \mathbf{a}} \left[ \frac{\partial^2}{\partial \theta^2} \ln p(\mathbf{r} | \mathbf{a}; \theta) \right] = \frac{2}{N_0} \sum_k E_{a_k} [ |a_k|^2 ] = \frac{2E_s K}{N_0}$$

## CRB for phase estimation : uncoded transmission

$$p(\mathbf{a}) = \prod_k p(a_k) \quad (\text{i.i.d. symbols})$$

$$\Rightarrow p(\mathbf{r}; \theta) = \prod_k p(r_k; \theta) = \prod_k E_{a_k} [p(r_k | a_k; \theta)]$$

$$\text{CRB}^{-1} = K \cdot E_{r_k} \left[ \left( \frac{\partial}{\partial \theta} \ln(E_{a_k} [p(r_k | a_k; \theta)]) \right)^2 \right]$$

$E_{a_k} [\cdot]$  : 1-D summation

$E_{r_k} [\cdot]$  : 1-D numerical integration

## CRB for phase estimation : coded transmission

$$\frac{\partial}{\partial \theta} \ln p(\mathbf{r}; \theta) = \sum_{\mathbf{a}} \left( \frac{\partial}{\partial \theta} \ln p(\mathbf{r} | \mathbf{a}; \theta) \right) p(\mathbf{a} | \mathbf{r}; \theta)$$

$$\mathbf{r} = \mathbf{a} \exp(j\theta) + \mathbf{w} \Rightarrow \frac{\partial}{\partial \theta} \ln p(\mathbf{r} | \mathbf{a}; \theta) = \frac{2}{N_0} \sum_k \text{Im}[a_k^* r_k \exp(-j\theta)]$$

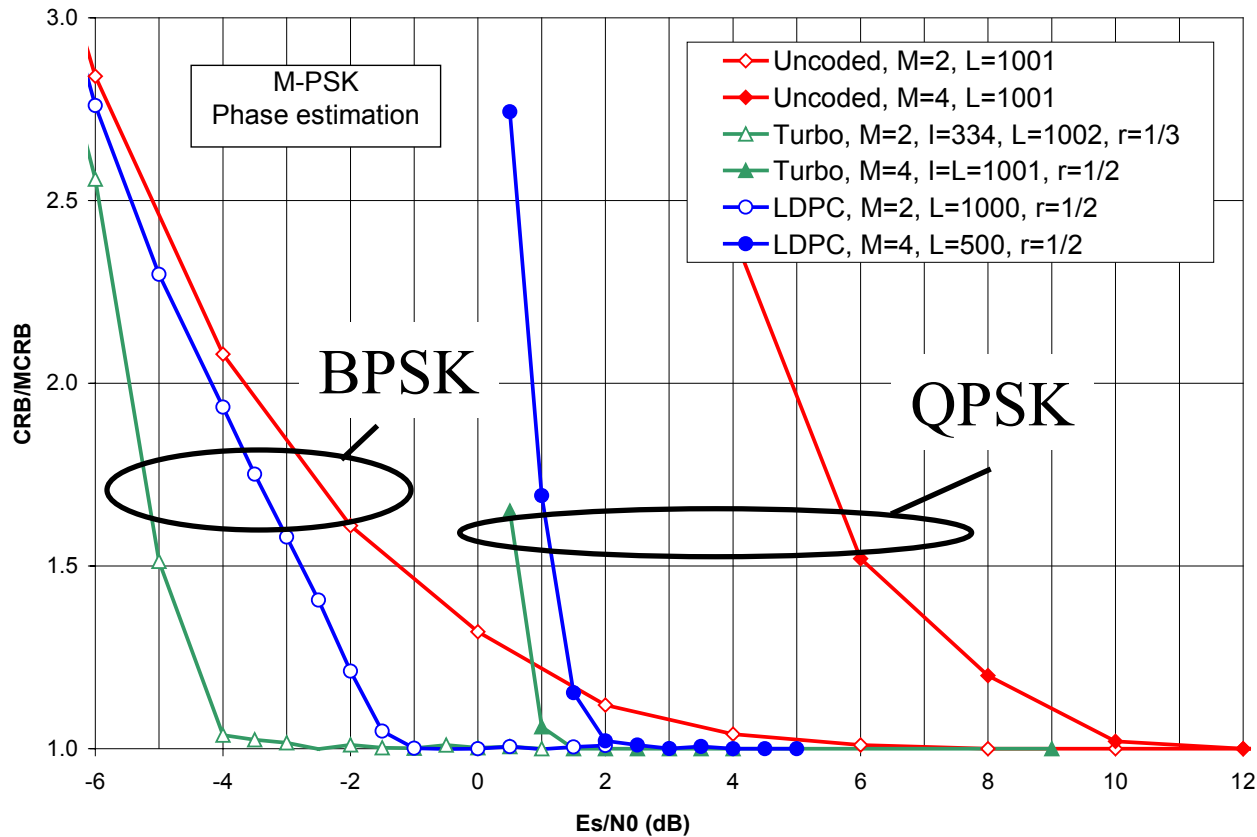
$$\frac{\partial}{\partial \theta} \ln p(\mathbf{r}; \theta) = \frac{2}{N_0} \sum_k \text{Im}[\tilde{a}_k^*(\mathbf{r}; \theta) r_k \exp(-j\theta)]$$

$$\tilde{a}_k(\mathbf{r}; \theta) = \sum_{\mathbf{a}} a_k p(\mathbf{a} | \mathbf{r}; \theta) = \sum_{a_k} a_k p(a_k | \mathbf{r}; \theta) \quad \begin{array}{l} \textit{marginal symbol APPs} \\ \text{(from MAP detector} \\ \text{operating on } \mathbf{r}) \end{array}$$

$$\text{CRB}^{-1} = E_{\mathbf{r}} \left[ \left( \frac{\partial}{\partial \theta} \ln p(\mathbf{r}; \theta) \right)^2 \right] \quad \begin{array}{l} E_{a_k | \mathbf{r}}[\cdot] : 1\text{-D summation per symbol} \\ E_{\mathbf{r}}[\cdot] : \text{Monte Carlo simulation} \end{array}$$

# CRB, MCRB : numerical results

TELIN



$$\text{MCRB} = \frac{N_0}{2LE_s}$$

(phase estimation)

Large SNR : CRB  $\rightarrow$  MCRB

Small SNR : CRB<sub>uncoded</sub> > CRB<sub>coded</sub> > MCRB

$\Rightarrow$  **code properties**  
should be exploited  
during estimation

## Computation of ML estimate

Direct application of ML estimation is complicated :

$$p(\mathbf{r} | \theta) \propto \sum_{\mathbf{b}} p(\mathbf{r} | \mathbf{a} = \chi(\mathbf{b}), \theta) \quad \text{many terms !}$$

$\Rightarrow$  compute ML estimate *iteratively* (**EM algorithm**) :  $\hat{\theta}_{\text{ML}} = \lim_{i \rightarrow \infty} \hat{\theta}^{(i)}$

$$\hat{\theta}^{(i+1)} = \arg \max_{\theta} E[p(\mathbf{r} | \mathbf{a}, \theta) | \mathbf{r}, \hat{\theta}^{(i)}] = \arg \left( \sum_{\mathbf{k}} \tilde{\mathbf{a}}_{\mathbf{k}}^{(i)*} z_{\mathbf{k}} \right)$$

$$\tilde{\mathbf{a}}_{\mathbf{k}}^{(i)} = E[\mathbf{a}_{\mathbf{k}} | \mathbf{r}, \hat{\theta}^{(i)}] \quad \text{soft decision (SD) on symbols}$$

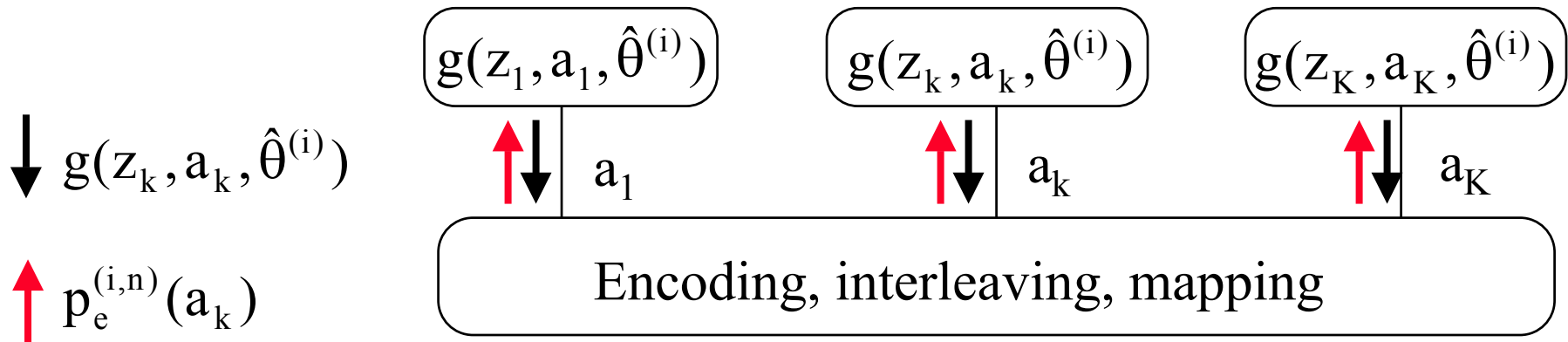
symbol APPs computed by *MAP detector*

## EM algorithm : symbol APP computation

outer iteration index  $i$  (EM algorithm),  
inner iteration index  $n$  (MAP detector)

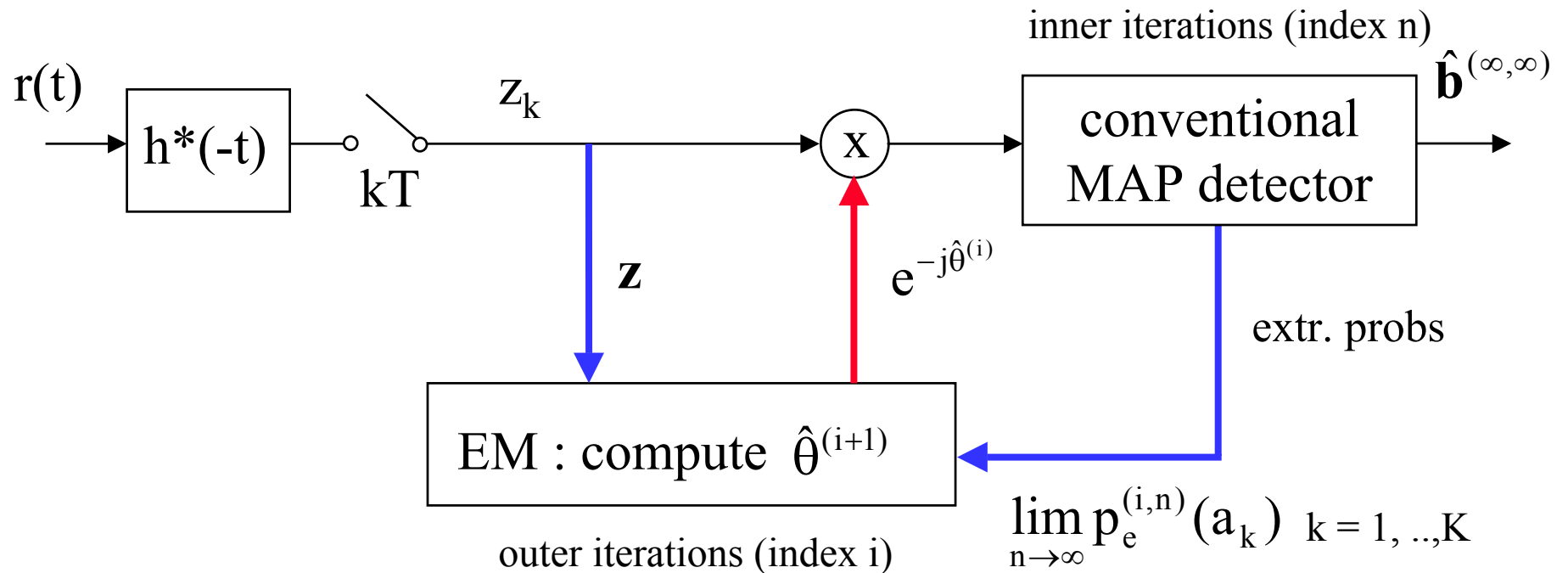
for each  $i$  :

MAP detector is reset and iterated *until convergence* ( $n \rightarrow \infty$ )



$$\text{symbol APP : } p(a_k | \mathbf{r}, \hat{\theta}^{(i)}) = g(z_k, a_k, \hat{\theta}^{(i)}) p_e^{(i,\infty)}(a_k) \Rightarrow \text{SD } \tilde{a}_k^{(i)}$$

## Receiver structure for EM algorithm



$$\text{symbol APP : } p(\mathbf{a}_k | \mathbf{r}, \hat{\theta}^{(i)}) = g(z_k, \mathbf{a}_k, \hat{\theta}^{(i)}) p_e^{(i, \infty)}(\mathbf{a}_k) \Rightarrow \text{SD } \tilde{\mathbf{a}}_k^{(i)}$$



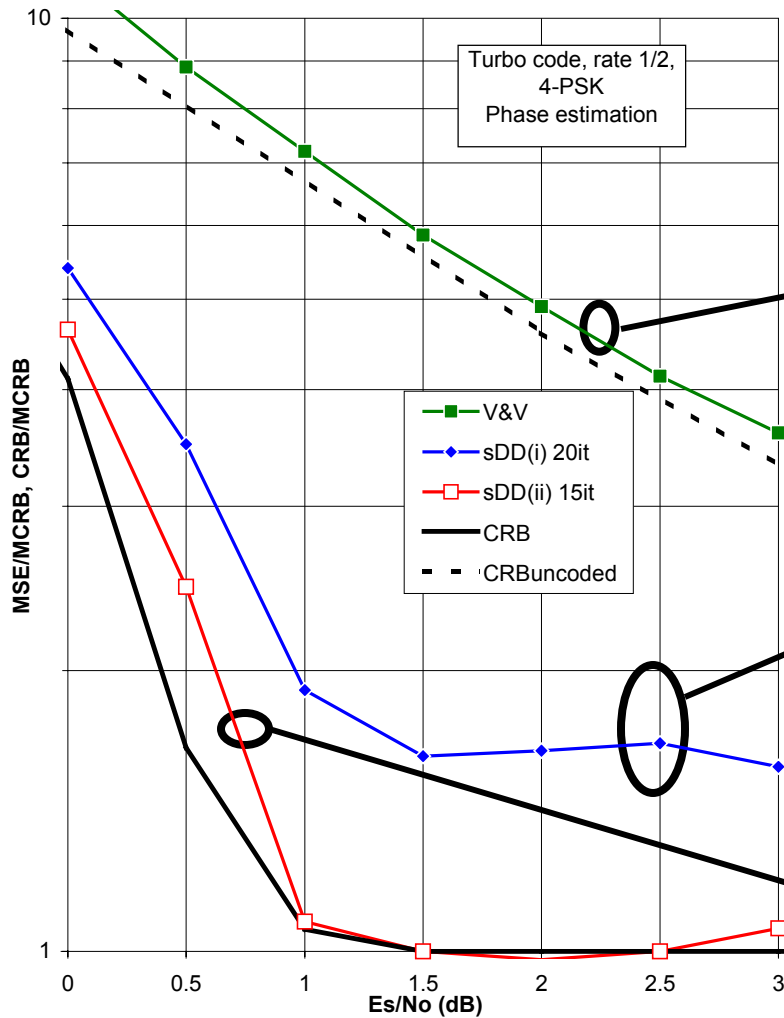
## Reduced-complexity EM algorithm

For each EM iteration, MAP detector is iterated till convergence  
 $\Rightarrow$  computational complexity too high

**Solution** : “merging” of EM iterations and MAP detector iterations.  
For each EM iteration, *only one* MAP detector iteration is performed,  
without resetting MAP detector  
 $\Rightarrow$  reduced complexity (at expense of reduced convergence speed)

$$\text{symbol APP : } p(\mathbf{a}_k | \mathbf{r}, \hat{\boldsymbol{\theta}}^{(i)}) \propto g(\mathbf{z}_k, \mathbf{a}_k, \hat{\boldsymbol{\theta}}^{(i)}) p_e^{(i,1)}(\mathbf{a}_k) \Rightarrow \text{SD } \tilde{\mathbf{a}}_k^{(i)}$$

# EM algorithm : exploiting code properties



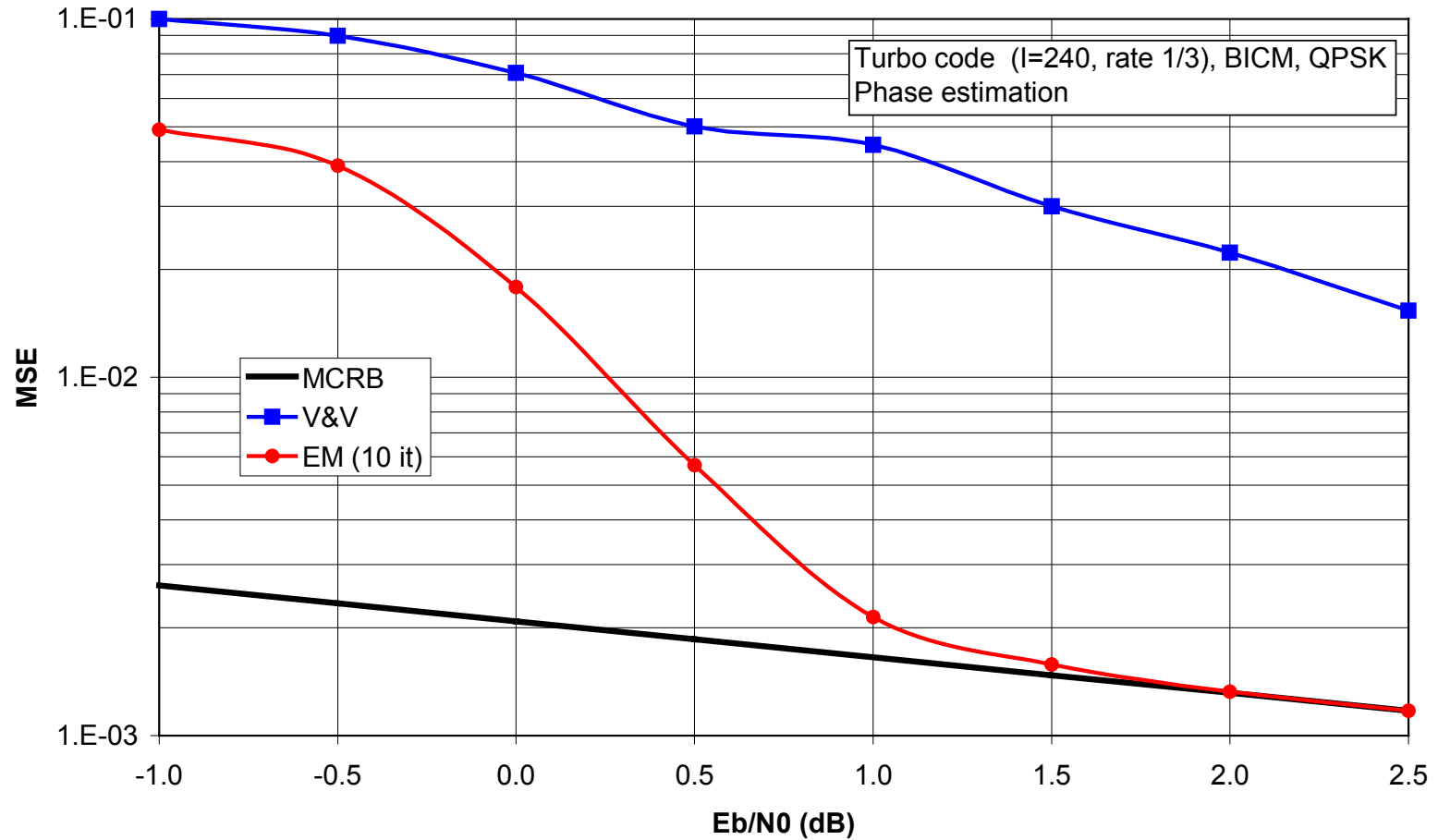
partial (or no) exploitation of code properties  $\Rightarrow$  degradation of MSE

does not exploit code properties

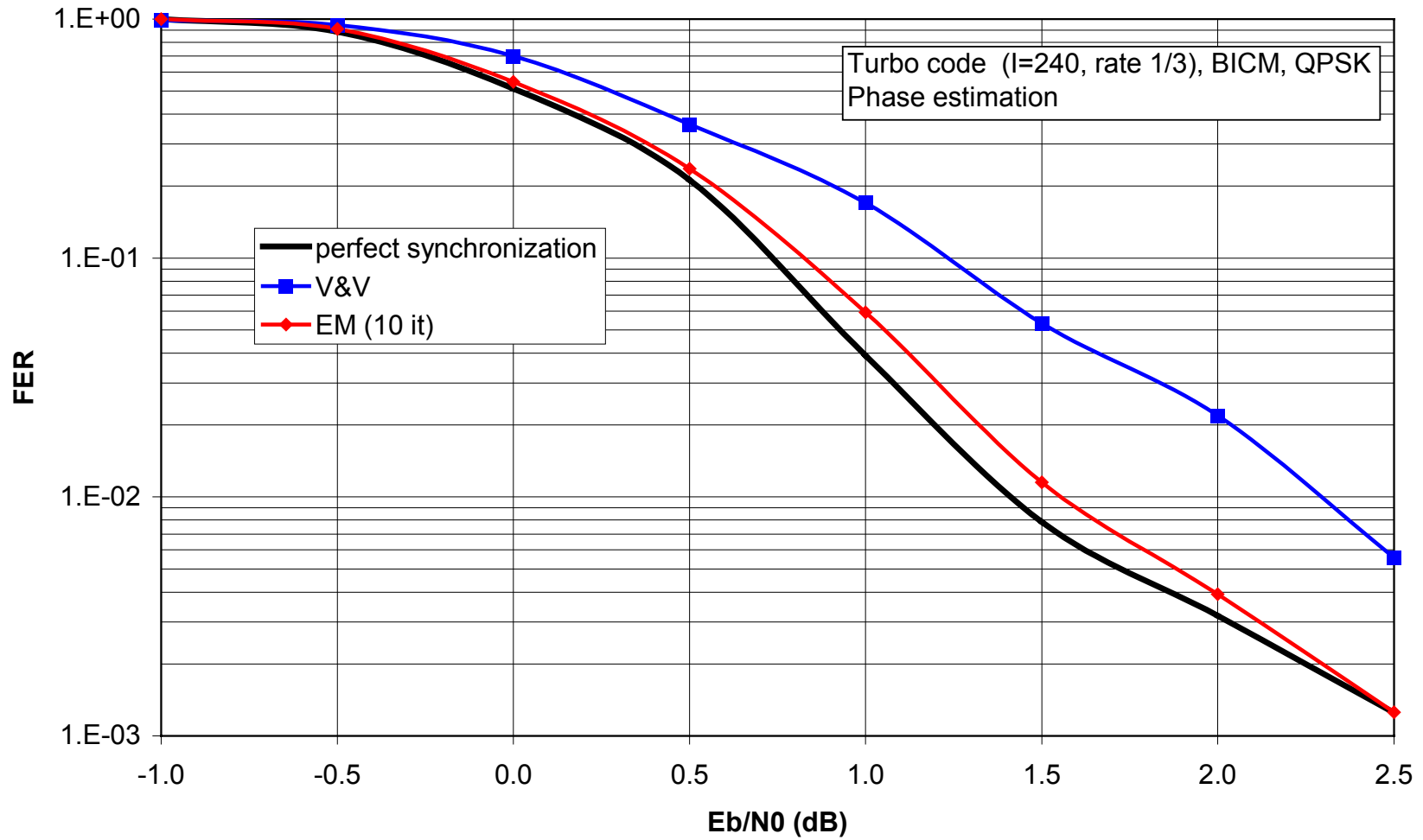
uses infobit APPs only,  
assumes parity bits are uncoded

uses infobit APPs and parity bit APPs

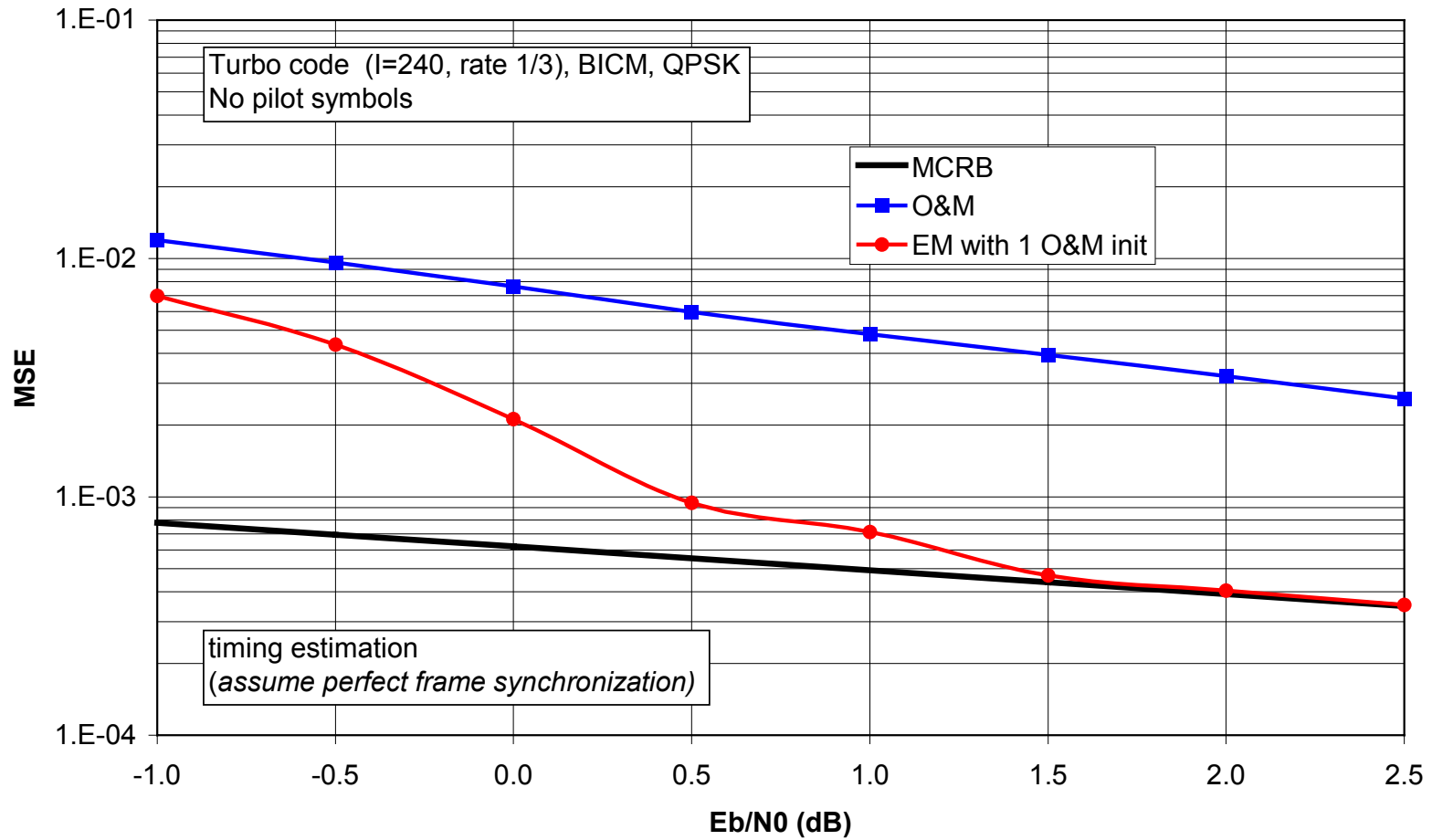
# EM algorithm : phase estimation (1/2)



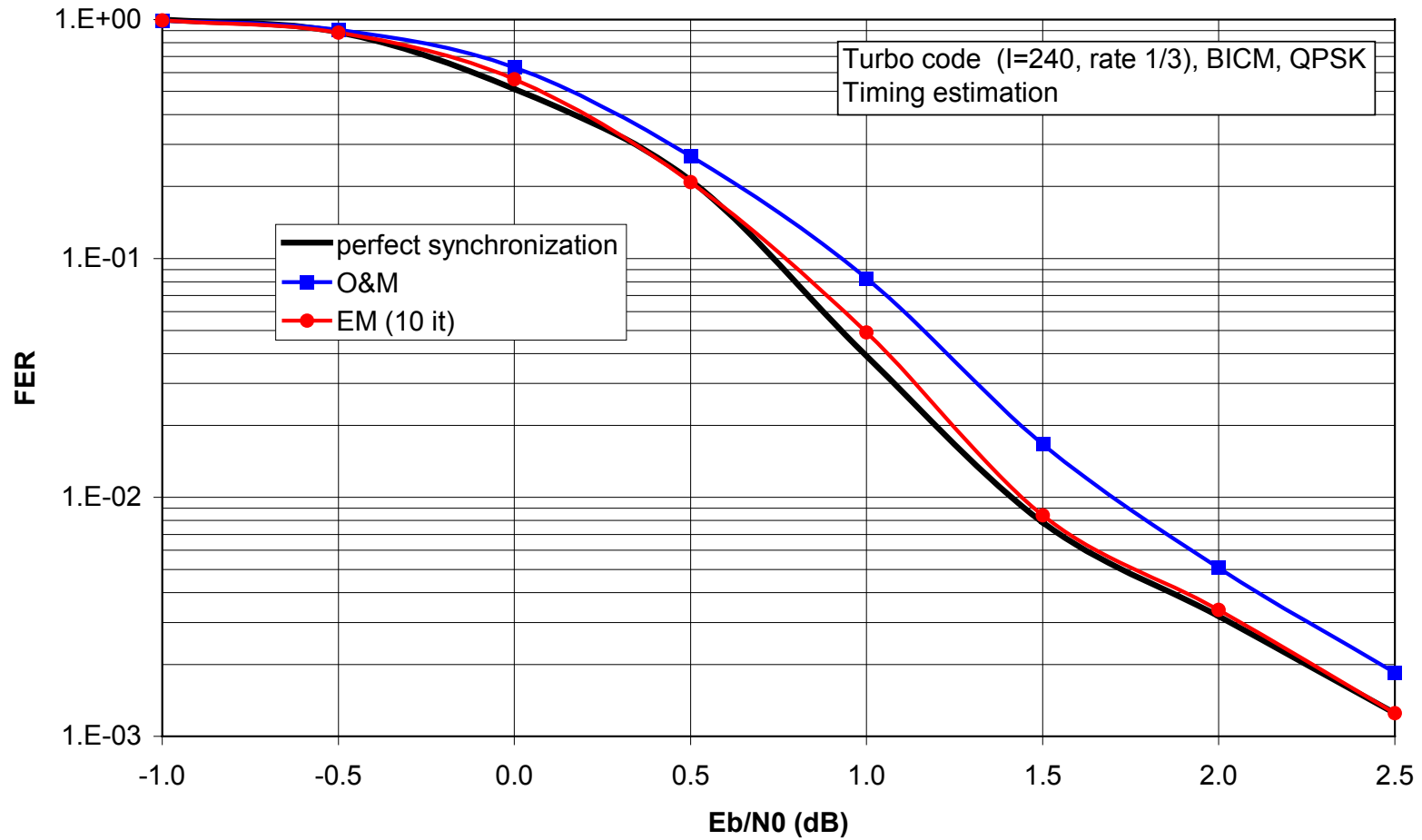
# EM algorithm : phase estimation (2/2)



# EM algorithm : timing estimation (1/2)



# EM algorithm : timing estimation (2/2)



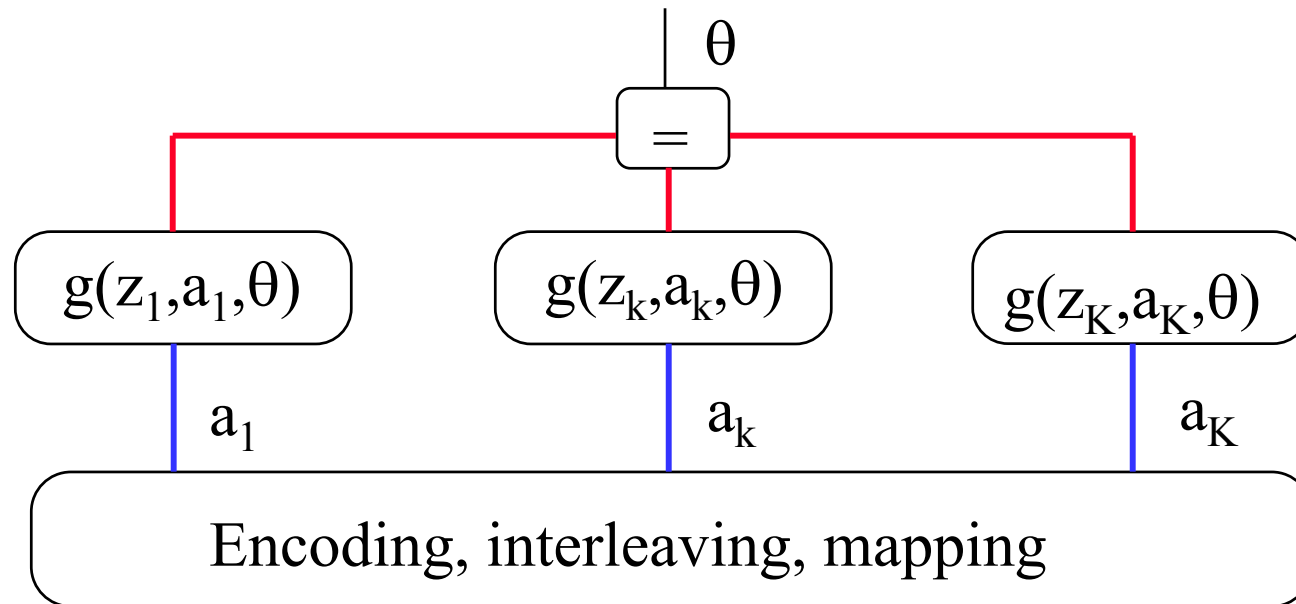
# **Alternative 2 :**

# **Simplified sum-product algorithm**

## Simplified sum-product algorithm

Factor graph corresponding to unknown  $\theta$

- messages are functions of  $\theta$
- downward messages involve integration over  $\theta$





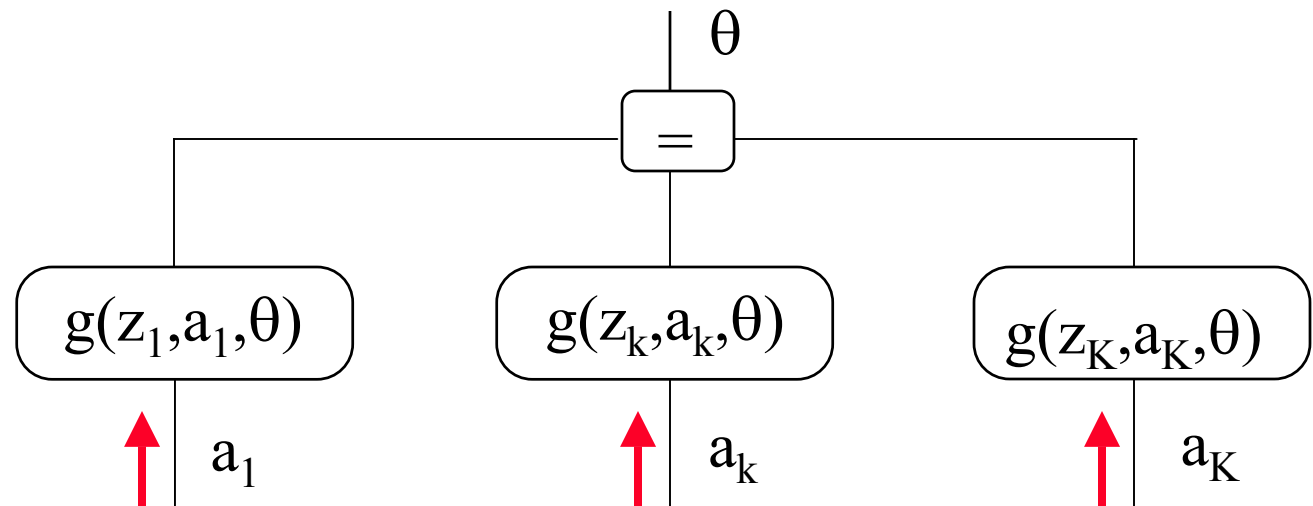
## Simplified sum-product algorithm

Messages depending on  $\theta$  are *approximated* by  $\delta(\theta - \hat{\theta}^{(n)})$   
 ( $n$  : iteration index of MAP detector)

$$\hat{\theta}^{(n)} = \arg \max_{\theta} p^{(n)}(\mathbf{r} | \theta) = \arg \max_{\theta} \sum_{\mathbf{a}} p(\mathbf{r} | \mathbf{a}; \theta) p_e^{(n)}(\mathbf{a})$$

$$p(\mathbf{r} | \mathbf{a}; \theta) = \prod_k g(z_k, \mathbf{a}_k, \theta) \qquad p_e^{(n)}(\mathbf{a}) = \prod_k p_e^{(n)}(\mathbf{a}_k)$$

↑  $p_e^{(n)}(\mathbf{a}_k)$



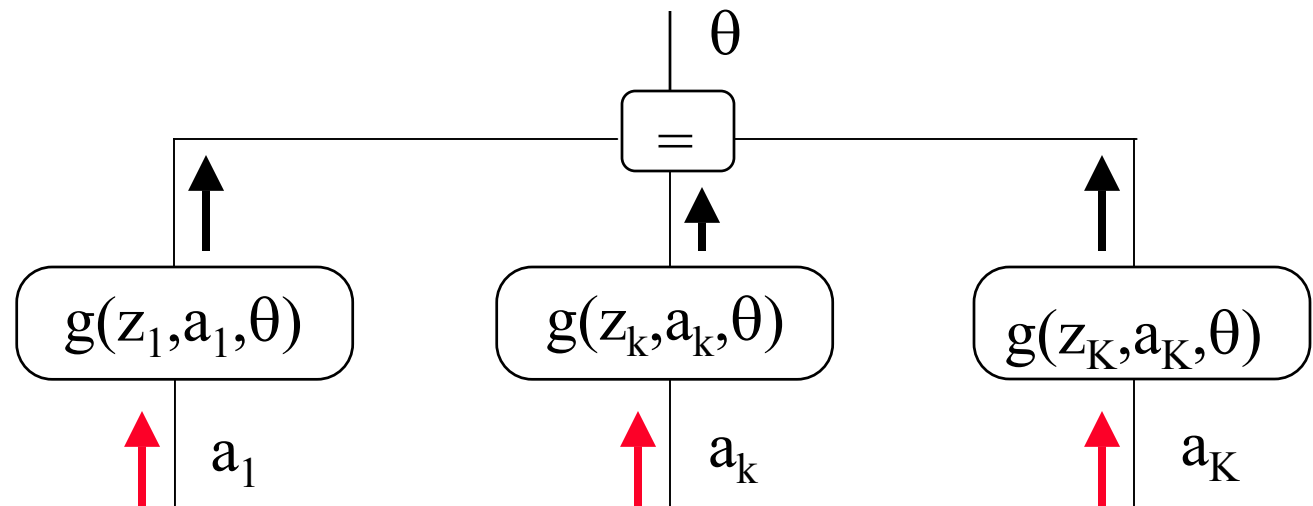
## Simplified sum-product algorithm

Messages depending on  $\theta$  are *approximated* by  $\delta(\theta - \hat{\theta}^{(n)})$   
 ( $n$  : iteration index of MAP detector)

$$\hat{\theta}^{(n)} = \arg \max_{\theta} p^{(n)}(\mathbf{r} | \theta) = \arg \max_{\theta} \sum_{\mathbf{a}} p(\mathbf{r} | \mathbf{a}; \theta) p_e^{(n)}(\mathbf{a})$$

$$p(\mathbf{r} | \mathbf{a}; \theta) = \prod_k g(z_k, \mathbf{a}_k, \theta) \qquad p_e^{(n)}(\mathbf{a}) = \prod_k p_e^{(n)}(\mathbf{a}_k)$$

↑  $p_e^{(n)}(\mathbf{a}_k)$

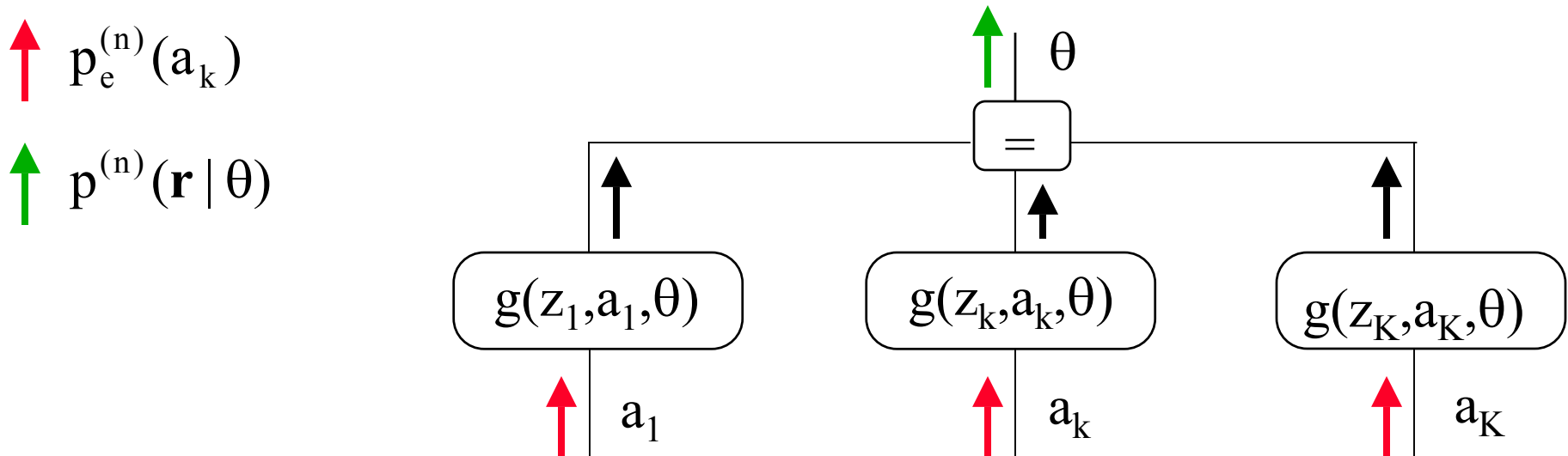


## Simplified sum-product algorithm

Messages depending on  $\theta$  are *approximated* by  $\delta(\theta - \hat{\theta}^{(n)})$   
 ( $n$  : iteration index of MAP detector)

$$\hat{\theta}^{(n)} = \arg \max_{\theta} p^{(n)}(\mathbf{r} | \theta) = \arg \max_{\theta} \sum_{\mathbf{a}} p(\mathbf{r} | \mathbf{a}; \theta) p_e^{(n)}(\mathbf{a})$$

$$p(\mathbf{r} | \mathbf{a}; \theta) = \prod_k g(z_k, \mathbf{a}_k, \theta) \qquad p_e^{(n)}(\mathbf{a}) = \prod_k p_e^{(n)}(\mathbf{a}_k)$$

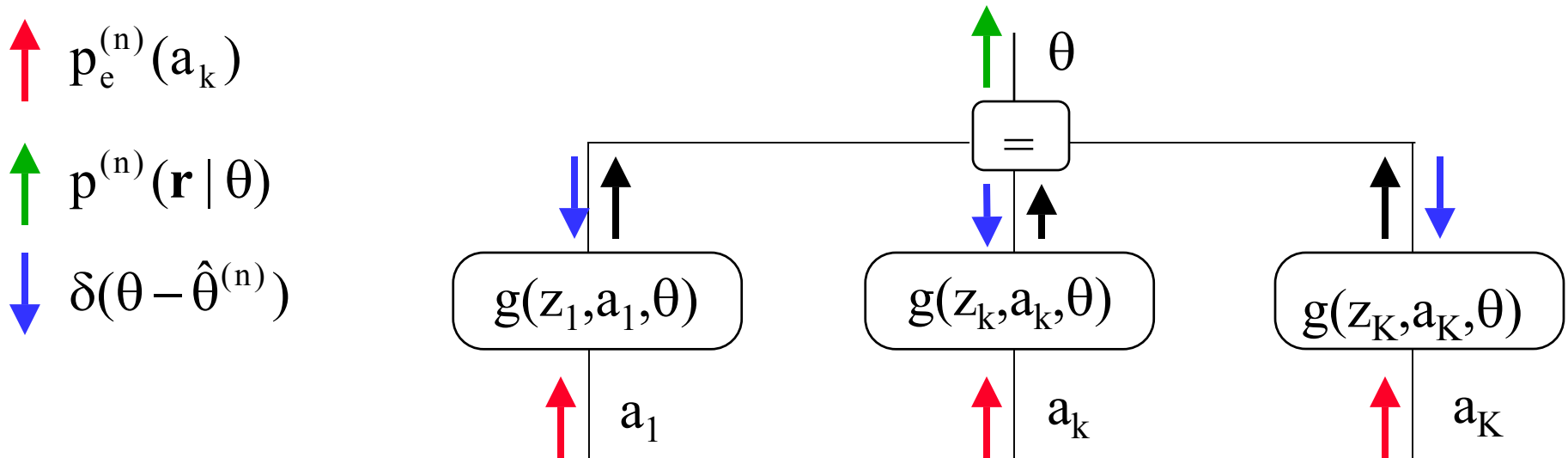


## Simplified sum-product algorithm

Messages depending on  $\theta$  are *approximated* by  $\delta(\theta - \hat{\theta}^{(n)})$   
 ( $n$  : iteration index of MAP detector)

$$\hat{\theta}^{(n)} = \arg \max_{\theta} p^{(n)}(\mathbf{r} | \theta) = \arg \max_{\theta} \sum_{\mathbf{a}} p(\mathbf{r} | \mathbf{a}; \theta) p_e^{(n)}(\mathbf{a})$$

$$p(\mathbf{r} | \mathbf{a}; \theta) = \prod_k g(z_k, a_k, \theta) \qquad p_e^{(n)}(\mathbf{a}) = \prod_k p_e^{(n)}(a_k)$$

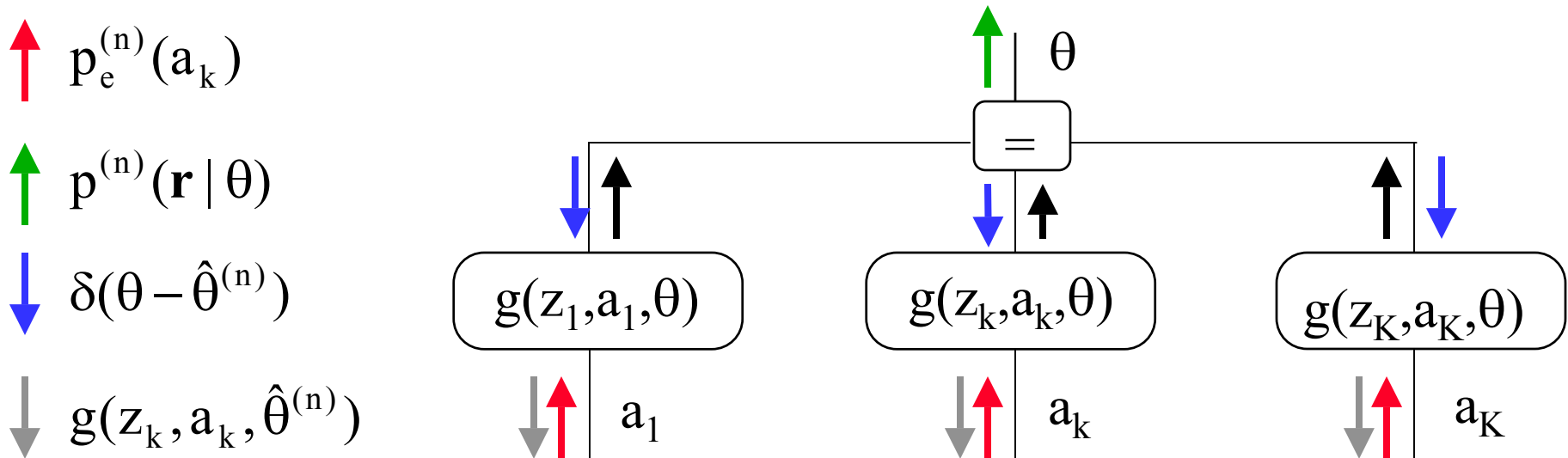


## Simplified sum-product algorithm

Messages depending on  $\theta$  are *approximated* by  $\delta(\theta - \hat{\theta}^{(n)})$   
 ( $n$  : iteration index of MAP detector)

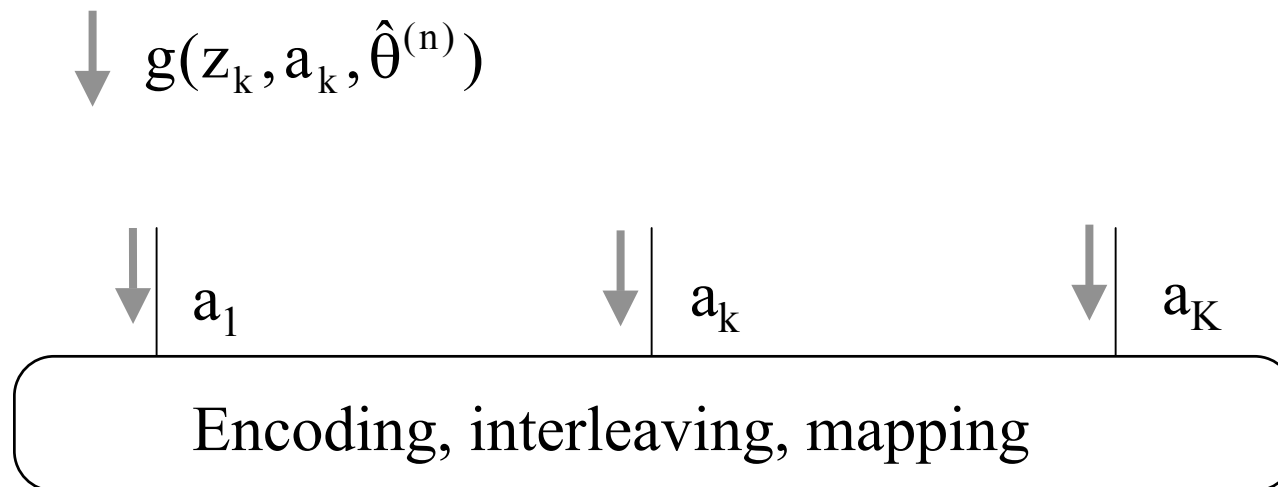
$$\hat{\theta}^{(n)} = \arg \max_{\theta} p^{(n)}(\mathbf{r} | \theta) = \arg \max_{\theta} \sum_{\mathbf{a}} p(\mathbf{r} | \mathbf{a}; \theta) p_e^{(n)}(\mathbf{a})$$

$$p(\mathbf{r} | \mathbf{a}; \theta) = \prod_k g(z_k, a_k, \theta) \qquad p_e^{(n)}(\mathbf{a}) = \prod_k p_e^{(n)}(a_k)$$



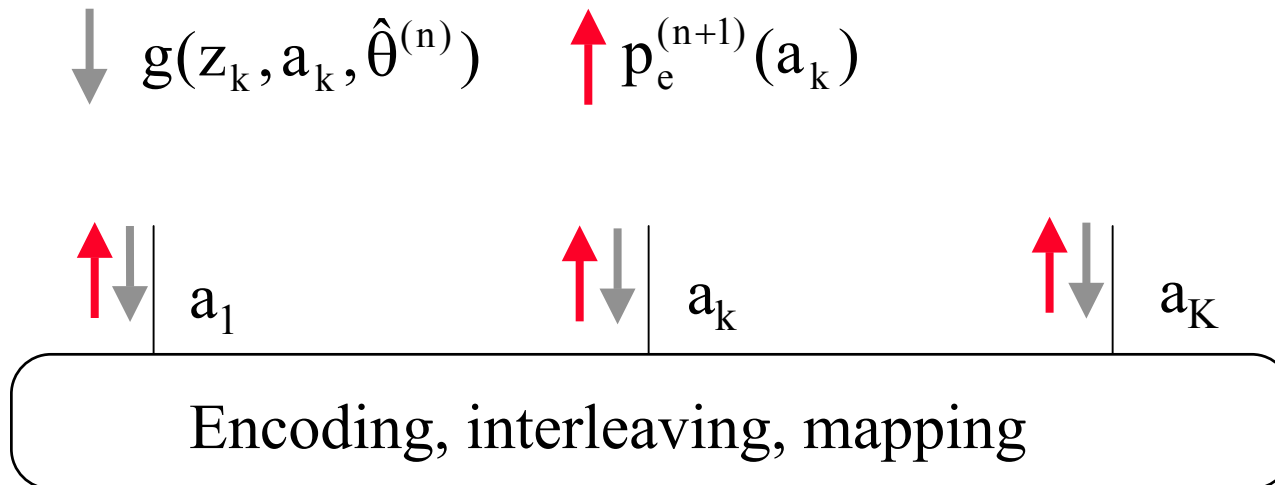
# Simplified sum-product algorithm

(n+1)-th iteration of MAP detector



# Simplified sum-product algorithm

(n+1)-th iteration of MAP detector



## Simplified sum-product algorithm : maximization of $p^{(n)}(\mathbf{r}|\theta)$

$$\hat{\theta}^{(n)} = \arg \max_{\theta} p^{(n)}(\mathbf{r} | \theta) = \arg \max_{\theta} \sum_{\mathbf{a}} p(\mathbf{r} | \mathbf{a}; \theta) p_e^{(n)}(\mathbf{a})$$

Similar to ML equation :  $p(\mathbf{a})$  is replaced by  $p_e^{(n)}(\mathbf{a})$

$\Rightarrow$  EM algorithm to maximize  $p^{(n)}(\mathbf{r}|\theta)$  iteratively  $\hat{\theta}^{(n)} = \lim_{i \rightarrow \infty} \hat{\theta}^{(n,i)}$

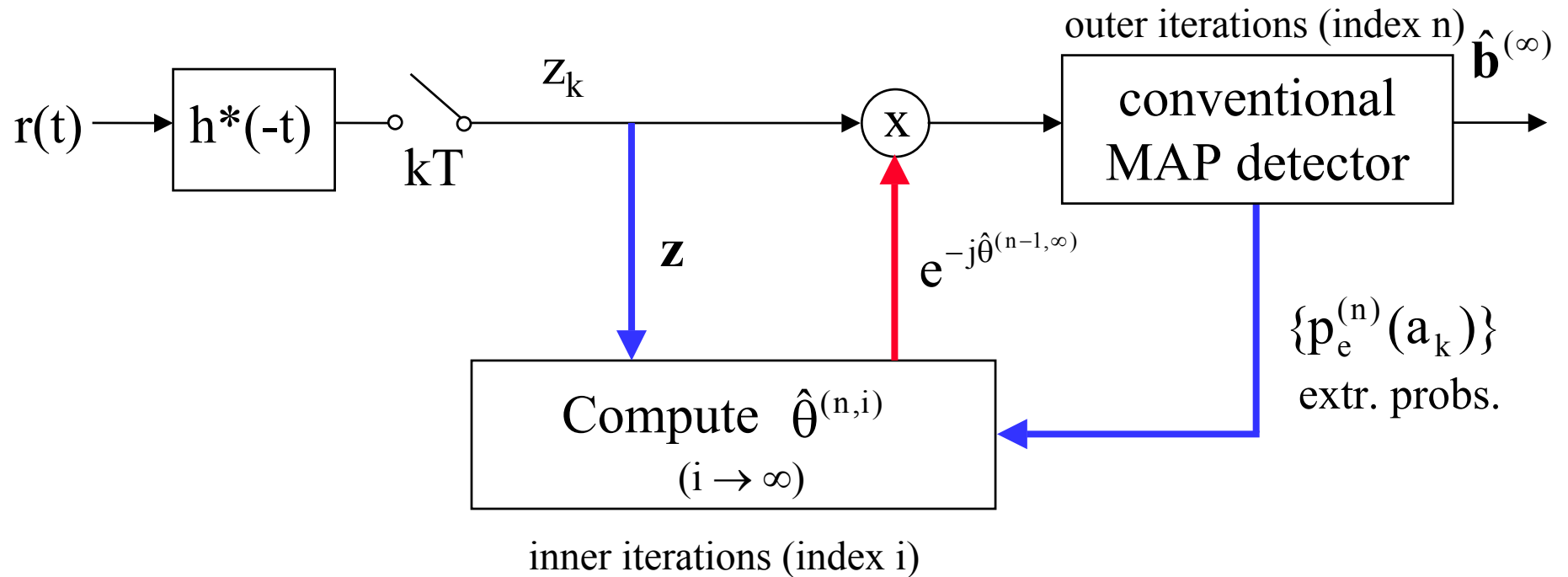
$$\hat{\theta}^{(n,i+1)} = \arg \max_{\theta} \sum_k E[g(z_k, \mathbf{a}_k, \theta | \mathbf{r}, \hat{\theta}^{(n,i)})] = \arg \left( \sum_k \tilde{\mathbf{a}}_k^{(n,i)*} z_k \right)$$

symbol APP :  $p^{(n)}(\mathbf{a}_k | \mathbf{r}; \hat{\theta}^{(n,i)}) \propto g(z_k, \mathbf{a}_k, \hat{\theta}^{(n,i)}) p_e^{(n)}(\mathbf{a}_k) \Rightarrow$  SD  $\tilde{\mathbf{a}}_k^{(n,i)}$



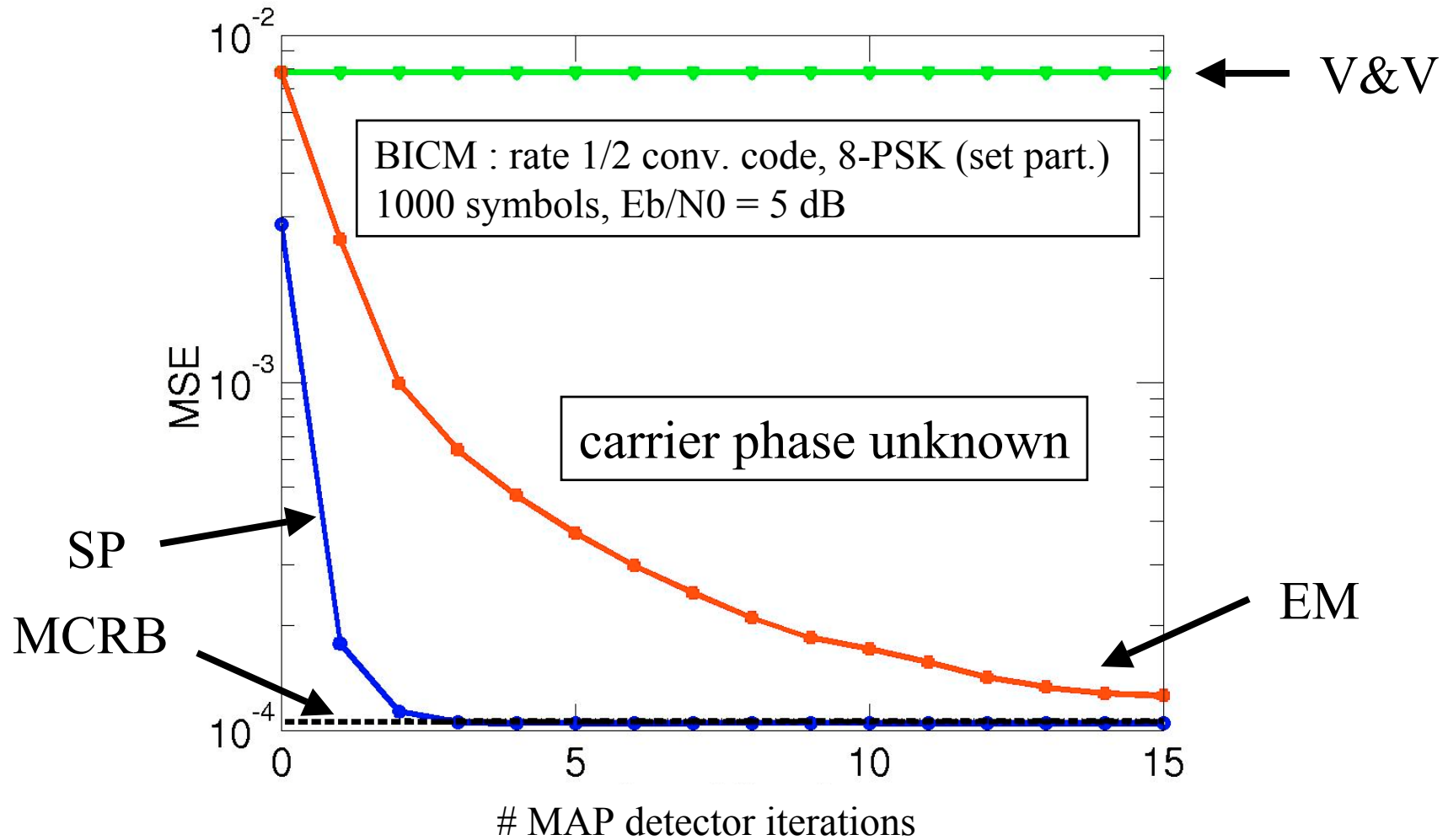
## Simplified sum-product algorithm : receiver structure

for each  $n$  : iterate EM algorithm until convergence ( $i \rightarrow \infty$ )

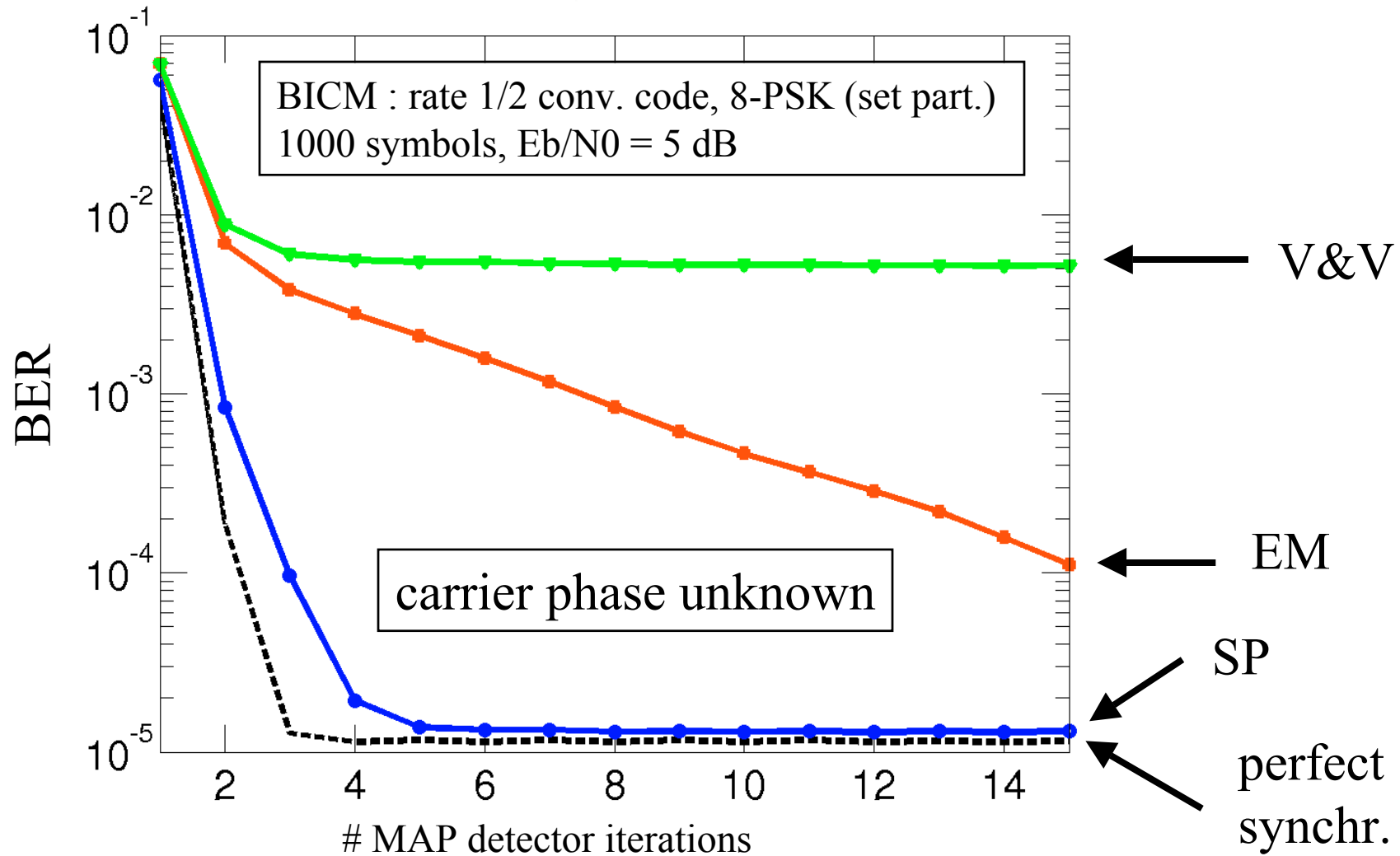


$$\text{symbol APP : } p^{(n)}(a_k | \mathbf{r}; \hat{\theta}^{(n,i)}) \propto g(z_k, a_k, \hat{\theta}^{(n,i)}) p_e^{(n)}(a_k) \Rightarrow \text{SD } \tilde{a}_k^{(n,i)}$$

# Simplified sum-product algorithm : estimator performance



# Simplified sum-product algorithm : BER performance



# Conclusions

Two alternatives for MAP detection when  $\theta$  is unknown

- Iterative ML estimation of  $\theta$  by means of EM algorithm

symbol APP during i-th EM iteration

$$\propto g(\mathbf{z}_k, \mathbf{a}_k, \hat{\theta}^{(i)}) p_e^{(i,1)}(\mathbf{a}_k)$$

one MAP detector iteration  
for each EM iteration

- Simplified SP algorithm (combined with EM algorithm)

symbol APP during i-th EM iteration of n-th MAP decoder iteration

$$\propto g(\mathbf{z}_k, \mathbf{a}_k, \hat{\theta}^{(n,i)}) p_e^{(n)}(\mathbf{a}_k)$$

EM algorithm iterated till convergence  
for each MAP decoder iteration

Both algorithms yield similar MSE and BER after convergence, but simplified SP algorithm requires considerably less MAP decoder iterations to converge.