

# Turbo Equalization

André Fonseca dos Santos  
Dayan Adionel Guimarães

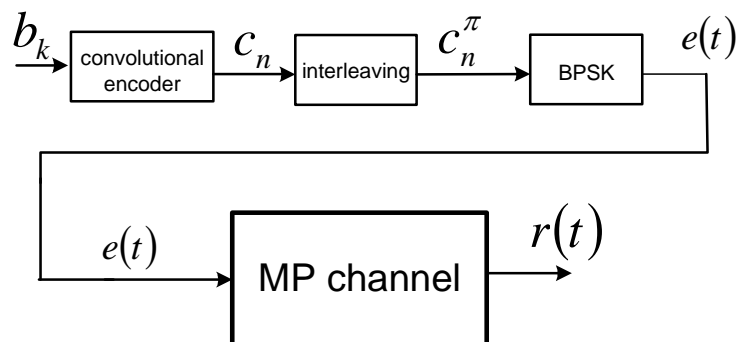
## Outline

- The discrete model of the channel with ISI.
- The turbo principle applied to iterative equalization and decoding: *Turbo Equalization*.
- The BCJR algorithm applied to equalization and convolutional decoding.
- Example of *Turbo Equalization*.
- Results and discussion.
- *Turbo Equalization* using the “Interference Canceler (IC)”.

## Introduction

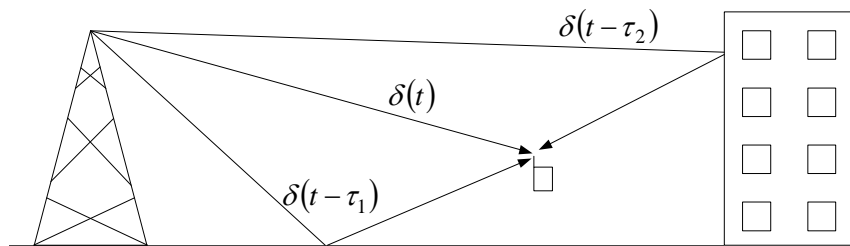
- Turbo codes were invented by Berrou, Glavieux and Thitimajshima in 1993 [Ber93].
- Turbo Equalization was proposed first by Douillard, Jezequel, Berrou, Picart, Didier, and Glavieux in 1995.
- A simplified Turbo Equalizer was proposed by Glavieux, Laot, and Labat in 1997.

## Transmission System



# Multipath Channel (MP)

**Inatel**  
Instituto Nacional de Telecomunicações

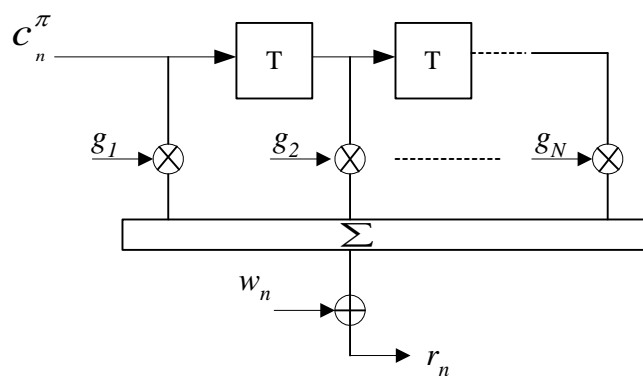


IWT 2004

5

# Multipath (MP) channel

**Inatel**  
Instituto Nacional de Telecomunicações



$g_n \rightarrow$  taps of the channel

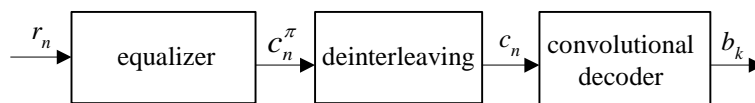
$w_n \rightarrow$  additive noise

IWT 2004

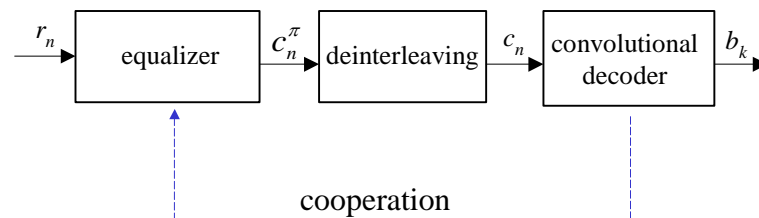
6

## Conventional system

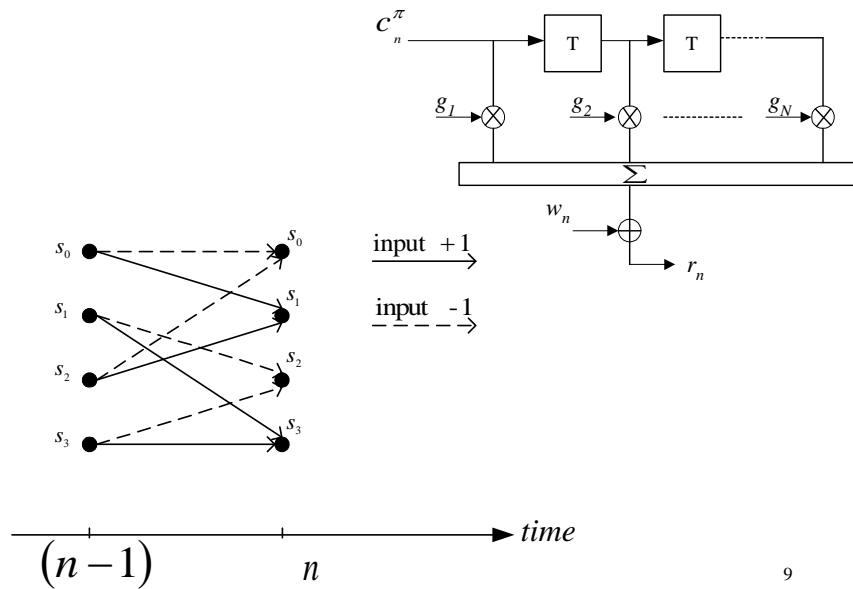
- Equalization and decoding separately.
  - Equalization: Filtering (LMS, DFE)  
MLSE (Viterbi Algorithm)



## Turbo Equalization



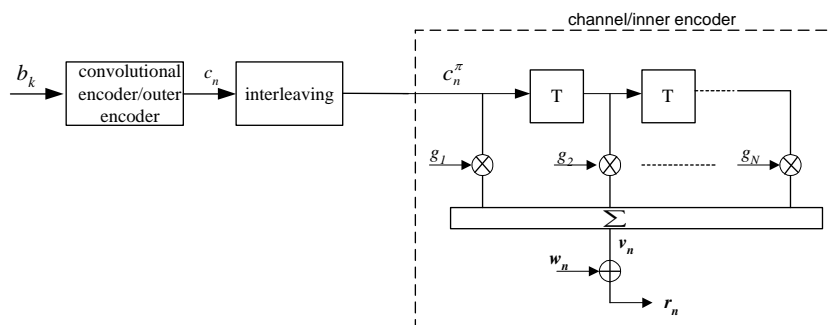
## MP channel as a Markov chain

**Inatel**  
 Instituto Nacional de Telecomunicações


IWT 2004

9

## Transmission model with MP channel

**Inatel**  
 Instituto Nacional de Telecomunicações


IWT 2004

10

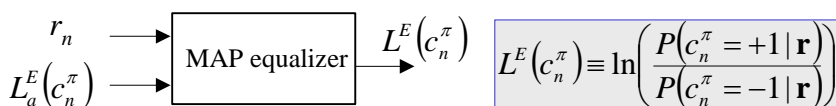
## SISO device



$$\text{Log-Likelihood Ratio (LLR)} = \ln \left( \frac{P(x = +1)}{P(x = -1)} \right)$$

- A hard decision can be done based on the signal of the LLR
- The reliability of the decision is related to by the magnitude of the LLR.

## Maximum A Posteriori (MAP) Equalizer



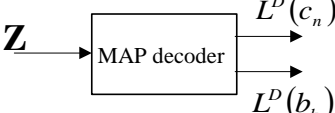
$$L^E(c_n^\pi) \equiv \ln \left( \frac{P(c_n^\pi = +1 | \mathbf{r})}{P(c_n^\pi = -1 | \mathbf{r})} \right), \text{ using Bayes' Rule:}$$

$$= \ln \left( \frac{p(\mathbf{r} | c_n^\pi = +1)}{p(\mathbf{r} | c_n^\pi = -1)} \right) + \ln \left( \frac{P(c_n^\pi = +1)}{P(c_n^\pi = -1)} \right) \equiv L_e^E(c_n^\pi) + L_a^E(c_n^\pi)$$

$L_e^E(c_n^\pi) \rightarrow$  Extrinsic Information  
 $L_a^E(c_n^\pi) \rightarrow$  A Priori Information



## MAP Decoder

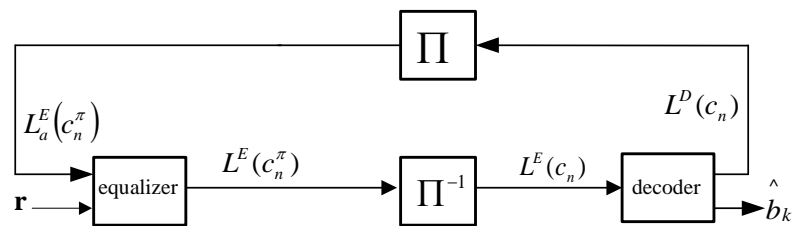
$$\mathbf{Z} \equiv [P(c_1 | \mathbf{r}) P(c_2 | \mathbf{r}) \dots P(c_N | \mathbf{r})]$$


$$L^D(c_n) \equiv \ln \left( \frac{P(c_n = +1 | \mathbf{Z})}{P(c_n = -1 | \mathbf{Z})} \right), \text{ using Bayes Rule :}$$

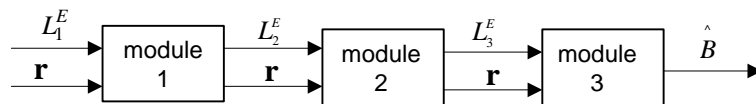
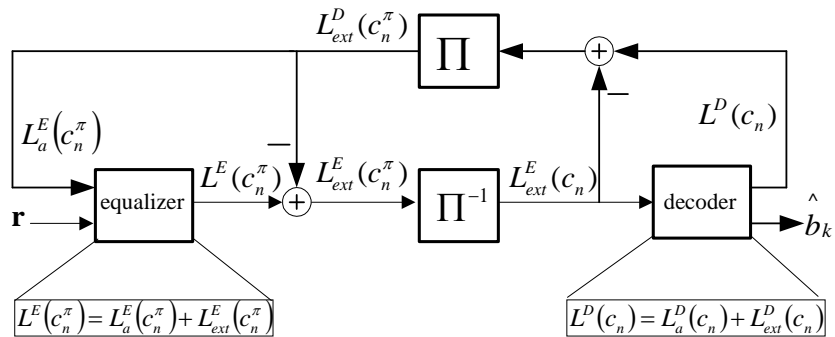
$$= \ln \left( \frac{p(\mathbf{Z} | c_n = +1)}{p(\mathbf{Z} | c_n = -1)} \right) + \ln \left( \frac{P(c_n = +1)}{P(c_n = -1)} \right) \equiv L_e^D(c_n) + L_a^D(c_n)$$

Also, the MAP decoder computes an estimate  $\hat{b}_k$  of the transmitted data as the most likely bit given  $\mathbf{Z}$ .

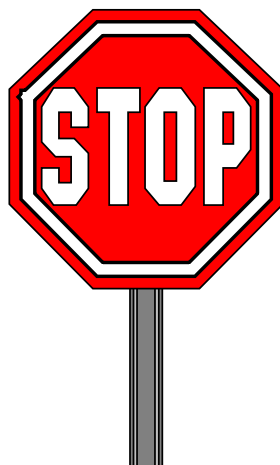
## Turbo Equalization (TuEqu)



## Turbo Equalization (TuEqu)



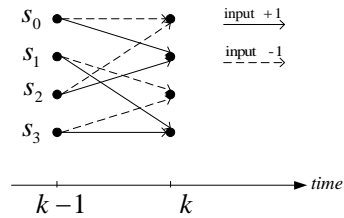
## Questions???





## MAP algorithm (BCJR)

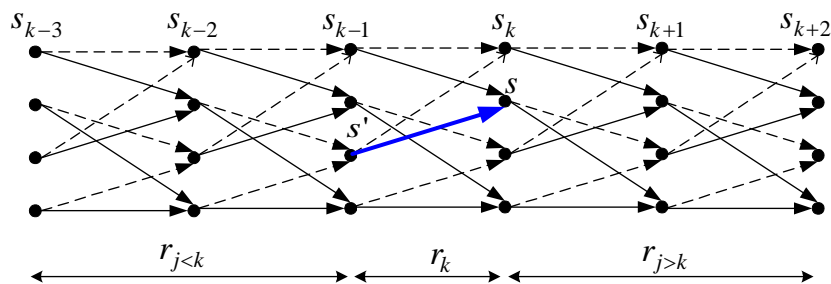
$$L(b_k) \equiv \ln \left( \frac{P(b_k = +1 | \mathbf{r})}{P(b_k = -1 | \mathbf{r})} \right)$$



using Bayes' rule:  $P(a, b) = P(a | b) P(b)$

$$L(b_k) = \ln \frac{p(b_k = +1, \mathbf{r})}{p(b_k = -1, \mathbf{r})}, \quad L(b_k) = \ln \frac{\left( \sum_{b_k = +1} p(s_{k-1}, s_k, \mathbf{r}) \right)}{\left( \sum_{b_k = -1} p(s_{k-1}, s_k, \mathbf{r}) \right)}$$

## MAP algorithm



$$p(s', s, \mathbf{r}) = p(s', s, r_{j < k}, r_k, r_{j > k})$$

# MAP algorithm

$$p(s', s, R) = p(s', s, r_{j < k}, r_k, r_{j > k})$$

Using Baye's rule :  $P(a, b) = P(a | b)P(b)$

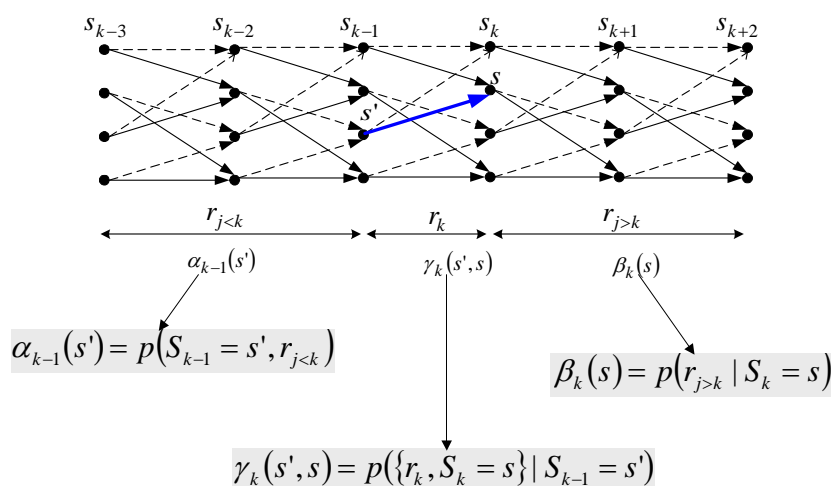
$$p(s', s, \mathbf{r}) = p(r_{j > k} | \{s', s, r_{j < k}, r_k\}) p(s', s, r_{j < k}, r_k)$$

Using the assumption that the channel is memoryless, the future received sequence  $r_{j > k}$  will only depend on the present state  $s$ :

$$\begin{aligned} P(s', s, \mathbf{r}) &= p(r_{j > k} | s) p(s', s, r_{j < k}, r_k) \\ &= p(r_{j > k} | s) p(\{r_k, s\} | \{s', r_{j < k}\}) p(s', r_{j < k}) \\ &= p(r_{j > k} | s) p(\{r_k, s\} | s') p(s', r_{j < k}) \end{aligned}$$

$$P(s', s, R) = \beta_k(s) \gamma_k(s', s) \alpha_{k-1}(s')$$

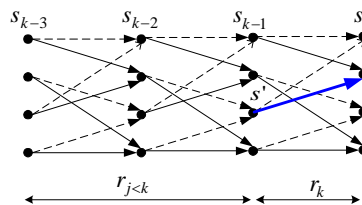
# MAP algorithm



# Forward recursive computation of $\alpha$

**Inatel**  
Instituto Nacional de Telecomunicações

$$\alpha_k(s) = p(S_k = s, r_{j < k+1})$$



$$\alpha_k(s) = p(s, r_{j < k}, r_k) = \sum_{\text{all } s'} p(s', s, r_{j < k}, r_k)$$

Using Bayes' rule and the assumption that the channel is memoryless:

$$\alpha_k(s) = \sum_{\text{all } s'} p(s', s, r_{j < k}, r_k) = \sum_{\text{all } s'} p(\{s, r_k\} | \{s', r_{j < k}\}) p(s', r_{j < k})$$

$$\alpha_k(s) = \sum_{\text{all } s'} p(\{s, r_k\} | s') p(s', r_{j < k})$$

Baye's rule:

$$P(a, b) = P(a | b) P(b)$$

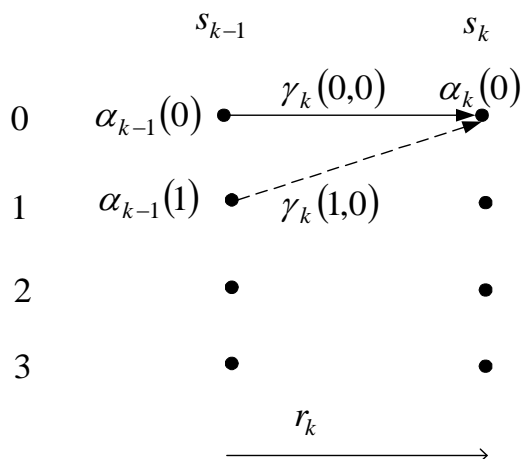
$$\alpha_k(s) = \sum_{\text{all } s'} \gamma_k(s', s) \alpha_{k-1}(s')$$

IWT 2004

21

# Forward recursive computation of $\alpha$

**Inatel**  
Instituto Nacional de Telecomunicações



$$\alpha_k(0) = \alpha_{k-1}(0) \gamma_k(0,0) + \alpha_{k-1}(1) \gamma_k(1,0)$$

IWT 2004

22

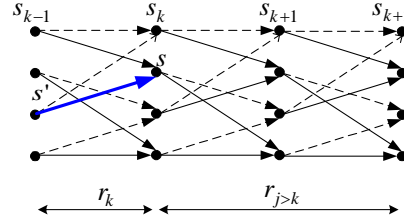
# Backward recursive computation of $\beta$

**Inatel**  
Instituto Nacional de Telecomunicações

$$\beta_{k-1}(s') = p(r_{j>k-1} | S_{k-1} = s')$$

$$\begin{aligned} \beta_{k-1}(s') &= p(r_{j>k-1} | s') \\ &= \sum_{all\ s} p(\{r_{j>k-1}, s\} | s') \\ &= \sum_{all\ s} p(\{r_{j>k}, r_k, s\} | s') \\ &= \sum_{all\ s} p(r_{j>k} | \{s, s', r_k\}) p(\{r_k, s\} | s') \\ &= \sum_{all\ s} p(r_{j>k} | \{s\}) p(\{r_k, s\} | s') \end{aligned}$$

$$\beta_{k-1}(s') = \sum_{all\ s} \beta_k(s) \gamma_k(s', s)$$



Baye's rule :

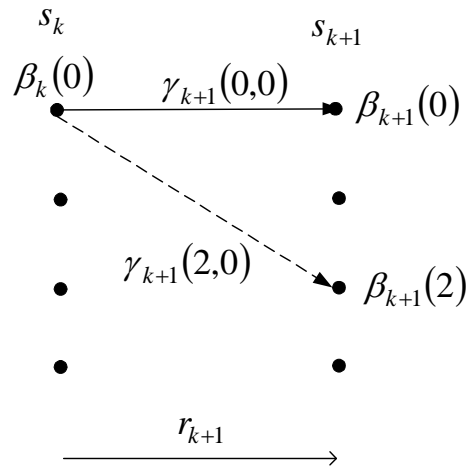
$$\begin{aligned} P(a, b) &= P(a | b) P(b) \\ P(\{a, b\} | c) &= P(a | (b, c)) P(b | c) \end{aligned}$$

IWT 2004

23

# Backward recursive computation of $\beta$

**Inatel**  
Instituto Nacional de Telecomunicações



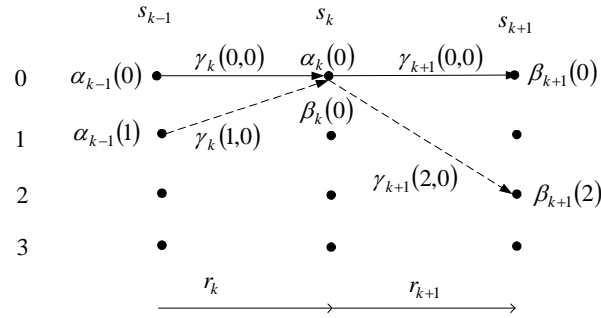
$$\beta_k(0) = \beta_{k+1}(0) \gamma_{k+1}(0,0) + \beta_{k+1}(2) \gamma_{k+1}(0,2)$$

IWT 2004

24

## MAP algorithm

$$\alpha_k(s) = \sum_{\text{all } s'} \gamma_k(s, s') \alpha_{k-1}(s') \quad , \quad \beta_{k-1}(s') = \sum_{\text{all } s} \gamma_k(s', s) \beta_k(s)$$



$$\alpha_k(0) = \alpha_{k-1}(0) \gamma_k(0,0) + \alpha_{k-1}(1) \gamma_k(1,0)$$

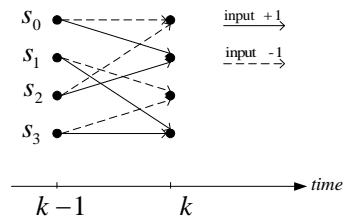
$$\beta_k(0) = \beta_{k+1}(0) \gamma_{k+1}(0,0) + \beta_{k+1}(2) \gamma_{k+1}(0,2)$$

IWT 2004

25

## MAP algorithm

$$L(b_k) \equiv \ln \left( \frac{P(b_k = +1 | \mathbf{r})}{P(b_k = -1 | \mathbf{r})} \right)$$

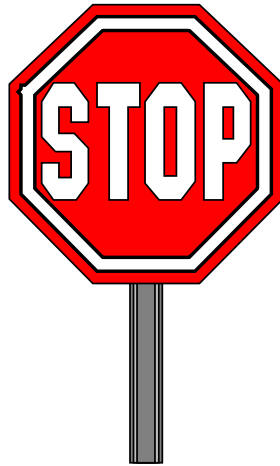


$$L(b_k) = \ln \frac{\left( \sum_{b_k=+1} p(S_{k-1}, S_k, \mathbf{r}) \right)}{\left( \sum_{b_k=-1} p(S_{k-1}, S_k, \mathbf{r}) \right)} = \ln \frac{\left( \sum_{b_k=+1} \alpha_{k-1}(s') \gamma_k(s', s) \beta_k(s) \right)}{\left( \sum_{b_k=-1} \alpha_{k-1}(s') \gamma_k(s', s) \beta_k(s) \right)}$$

IWT 2004

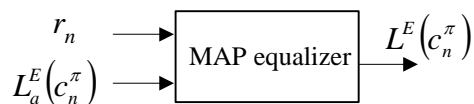
26

## Questions???



## MAP Equalizer

$$L^E(c_n^\pi) \equiv \ln \left( \frac{P(c_n^\pi = +1 | \mathbf{r})}{P(c_n^\pi = -1 | \mathbf{r})} \right)$$



$$\gamma_n(s', s) = p(\{r_n, S_n = s\} | S_{n-1} = s')$$

Baye's rule :

$$P(a, b) = P(a | b) \cdot P(b)$$

$$P(\{a, b\} | c) = P(a | (b, c)) \cdot P(b | c)$$

Using Baye's rule :

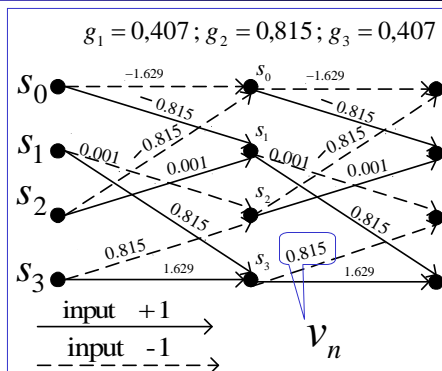
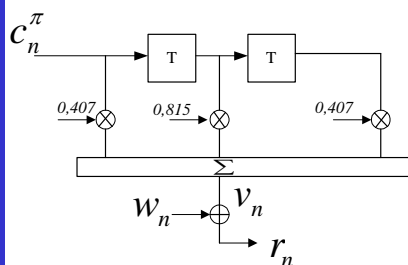
$$\gamma_n(s', s) = p(r_n | \{s, s'\}) \cdot P(s | s')$$

is governed by the output symbol

is governed by the input symbol



# MAP Equalizer



$$\gamma_n(s', s) = p(r_n | \{s, s'\}) \cdot P(s | s')$$

$$\gamma_n(s', s) = p(r_n | v_n) \cdot P(c_n^\pi)$$

$$p(r_n | v_n) = \exp(-(r_n - v_n)^2 / 2\sigma^2) / \sqrt{2\pi\sigma^2}$$

# MAP Equalizer

$$\gamma(s', s) = P(c_n^\pi) \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-(r_n - v_n)^2 / 2\sigma^2)$$

obtained from the extrinsic information  $L_{ext}^D(c_n)$  of the decoder :

$$L_{ext}^D(c_n) \cong \ln \frac{P(c_n^\pi = +1)}{P(c_n^\pi = -1)}$$

$$L_{ext}^D(c_n^\pi) \cong \ln \frac{P(c_n^\pi = +1)}{1 - P(c_n^\pi = +1)}$$

$$P(c_n^\pi = +1) \cong \frac{\exp(L_{ext}^D(c_n^\pi))}{1 + \exp(L_{ext}^D(c_n^\pi))}$$

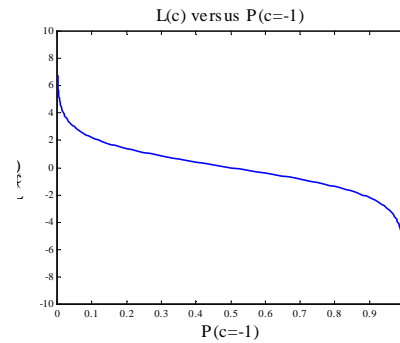
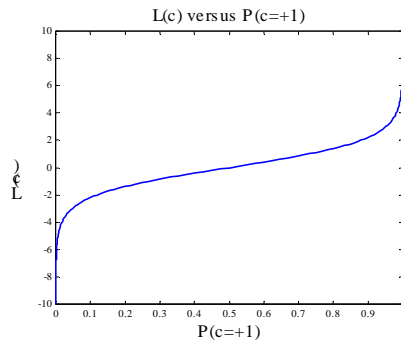
$$L_{ext}^D(c_n^\pi) \cong \ln \frac{1 - P(c_n^\pi = -1)}{P(c_n^\pi = +1)}$$

$$P(c_n^\pi = -1) \cong \frac{1}{1 + \exp(L_{ext}^D(c_n^\pi))}$$

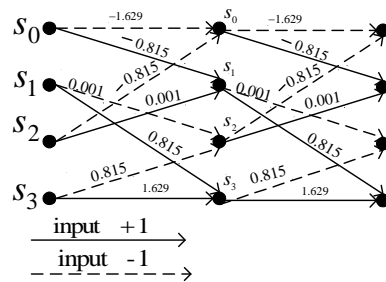
$$P(c_n^\pi = c) \cong \frac{\exp(c \cdot L_{ext}^D(c_n^\pi))}{1 + \exp(L_{ext}^D(c_n^\pi))} \quad c \in \{0, 1\}$$

# MAP Equalizer

$$\gamma(s', s) = \frac{\exp(c \cdot L_{ext}^D(c_n^\pi))}{1 + \exp(L_{ext}^D(c_n^\pi))} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(r_n - v_n)^2}{2\sigma^2}\right) \quad c \in \{0, 1\}$$



## MAP Equalizer implementation [Koetter]



$$\mathbf{A}(+1) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{A}(-1) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\{\mathbf{P}\}_{i,j,n} = \gamma_n(s_i, s_j, n)$$

$$\{\mathbf{B}\}_{i,j,n} \rightarrow \text{componentwise product of } A \text{ and } P$$



## MAP Equalizer implementation *Inatel* Instituto Nacional de Telecomunicações

Input : Matrices  $\mathbf{P}_n$ ,  $\mathbf{A}(+1)$ ,  $\mathbf{A}(-1)$ ,  $\mathbf{B}_n(+1)$ ,  $\mathbf{B}_n(-1)$ ,  $\mathbf{f}_n$  e  $\mathbf{b}_n$ .

Initialization: the first column of vector  $\mathbf{f}$  and the last of vector  $\mathbf{b}$  are initialized as 1 for every lines.

Recursively compute of  $\mathbf{f}$  and  $\mathbf{b}$  :

$$\mathbf{f}_n = \mathbf{P}_{n-1}^T \mathbf{f}_{n-1}, \quad n = 1, \dots, N$$

$$\mathbf{b}_n = \mathbf{P}_n \mathbf{b}_{n+1}, \quad n = N-1, \dots, 1$$

Output : for  $n = 1, \dots, N$

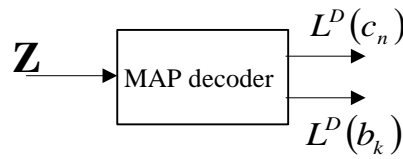
$$L^E(c_n^\pi | \mathbf{r}) = \ln \frac{\mathbf{f}_n^T \mathbf{B}_n(+1) \mathbf{b}_{n+1}}{\mathbf{f}_n^T \mathbf{B}_n(-1) \mathbf{b}_{n+1}} \quad L^E(c_n^\pi | \mathbf{r}) = \ln \frac{\left( \sum_{c_n^\pi=+1} \alpha_{n-1}(s') \gamma_n(s', s) \beta_n(s) \right)}{\left( \sum_{c_n^\pi=-1} \alpha_{n-1}(s') \gamma_n(s', s) \beta_n(s) \right)}$$

IWT 2004

33



## MAP Decoder *Inatel* Instituto Nacional de Telecomunicações



$$L^D(c_n) \equiv \ln \left( \frac{P(c_n = +1 | \mathbf{Z})}{P(c_n = -1 | \mathbf{Z})} \right) = L_e^D(c_n) + L_a^D(c_n)$$

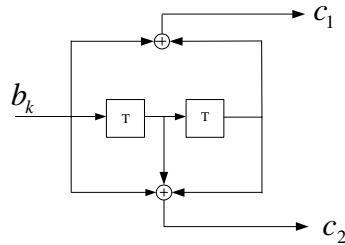
$$P(c_n | \mathbf{r}) \cong \frac{\exp(c \cdot L_{ext}^E(c_n))}{1 + \exp(L_{ext}^E(c_n))} \quad c \in \{0, 1\}$$

$$\mathbf{Z} = [P(c_1 | \mathbf{r}) P(c_2 | \mathbf{r}) \dots P(c_N | \mathbf{r})]^T$$

IWT 2004

34

## MAP Decoder



$$\gamma_n(s', s) = p(\{r_n, S_n = s\} | S_{n-1} = s')$$

Using Baye's rule :

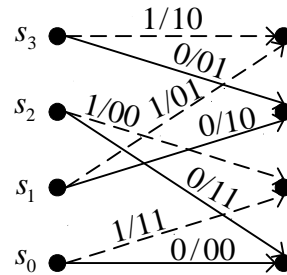
$$\gamma_n(s', s) = p(r_n | \{s, s'\}) P(s | s')$$

is governed by the output symbol

is governed by the input symbol

$$\gamma(s_i, s_j) = P(b_k) P(c_1 = c_{1,i,j} | \mathbf{r}) P(c_2 = c_{2,i,j} | \mathbf{r})$$

there is no a priori information of the information bits

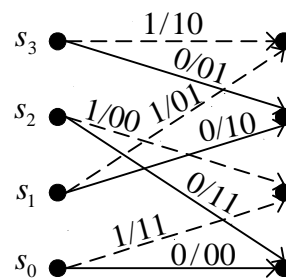


## MAP Decoder implementation [Koetter]

$$\mathbf{A}_b(1) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{A}_b(0) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\mathbf{A}_{c_1}(1) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{A}_{c_1}(0) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\mathbf{A}_{c_2}(1) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \quad \mathbf{A}_{c_2}(0) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$



## MAP Decoder implementation

Input : Matrices  $\mathbf{P}_n, \mathbf{A}(+1), \mathbf{A}(0), \mathbf{B}_n(+1), \mathbf{B}_n(0), \mathbf{f}_n, \mathbf{e}, \mathbf{b}_n$ .

for  $b, c_1$  and  $c_2$

Initialization: the first column of vector  $\mathbf{f}$  and the last of vector  $\mathbf{b}$  are initialized as 1 for every lines.

Recursively compute of  $\mathbf{f}$  and  $\mathbf{b}$ :

$$\mathbf{f}_n = \mathbf{P}_{n-1}^T \mathbf{f}_{n-1}, \quad n = 1, \dots, N$$

$$\mathbf{b}_n = \mathbf{P}_n \mathbf{b}_{n+1}, \quad n = N-1, \dots, 1$$

Output : for  $n = 1, \dots, N$

$$L^D(c_n | \mathbf{r}) = \ln \frac{\mathbf{f}_n^T \mathbf{B}_n(+1) \mathbf{b}_{n+1}}{\mathbf{f}_n^T \mathbf{B}_n(-1) \mathbf{b}_{n+1}}$$

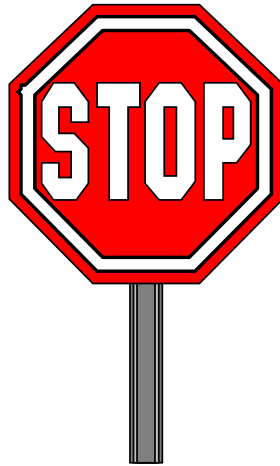
$$L^D(c_n | \mathbf{r}) = \ln \left( \frac{\sum_{c_n=+1} \alpha_{n-1}(s') \gamma_n(s', s) \beta_n(s)}{\sum_{c_n=-1} \alpha_{n-1}(s') \gamma_n(s', s) \beta_n(s)} \right)$$



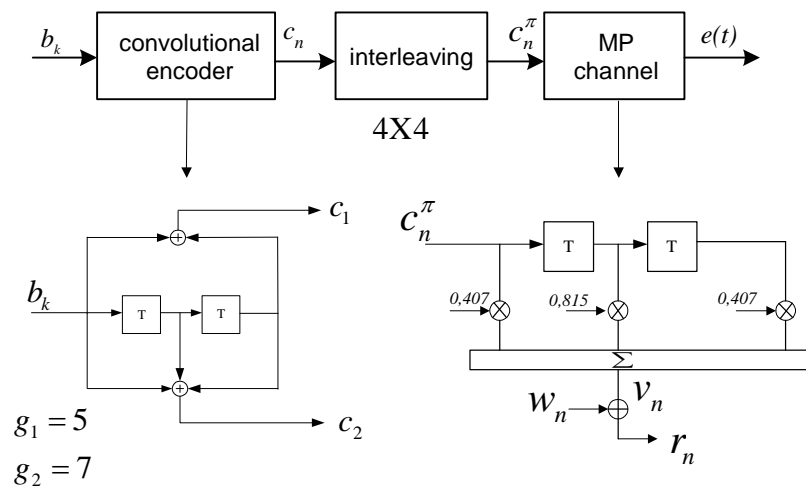
## MAP implementation

- For a practical implementation, the vectors *forward* and *backward* need to be normalized to avoid underflow.
- The *MAP algorithm* can be implemented in the log domain (Log-MAP-algorithm) for computational simplicity.

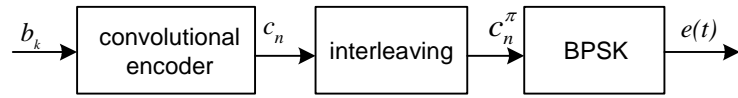
## Questions???



## TuEqu example



## TuEqu example

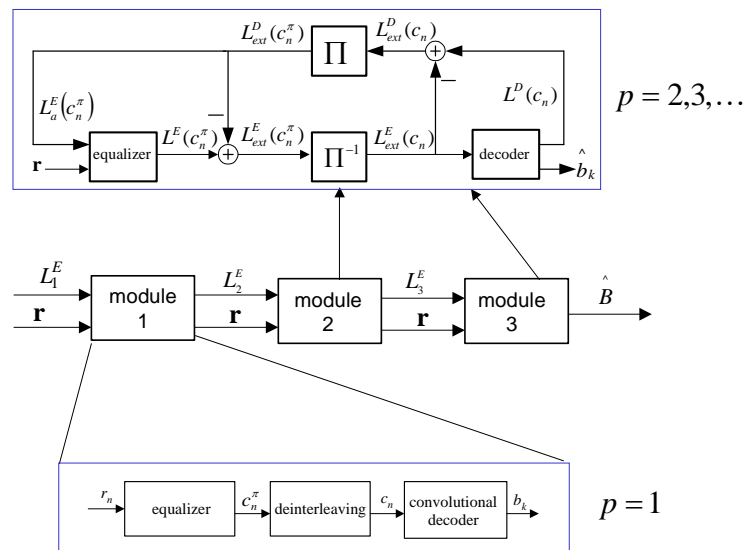


$$b_k = [1 \ 1 \ 0 \ 1 \ 0 \ 0 \ 1 \ 0]$$

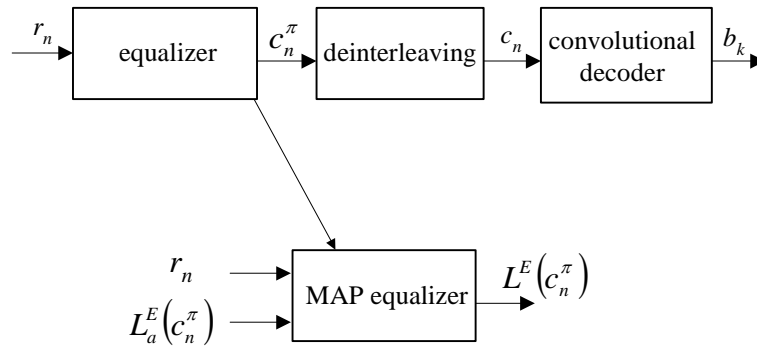
$$c_n = [1 \ 1 \ -1 \ 1 \ -1 \ 1 \ -1 \ -1 \ 1 \ -1 \ 1 \ -1 \ 1 \ 1 \ 0]$$

$$c_n^\pi = [1 \ -1 \ 1 \ 1 \ 1 \ 1 \ -1 \ 1 \ -1 \ -1 \ 1 \ 1 \ 1 \ -1 \ -1]$$

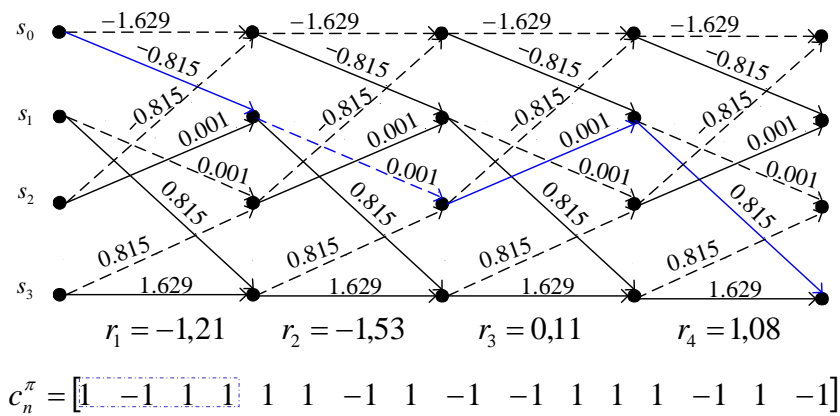
## TuEqu example



## TuEqu example (p=1)

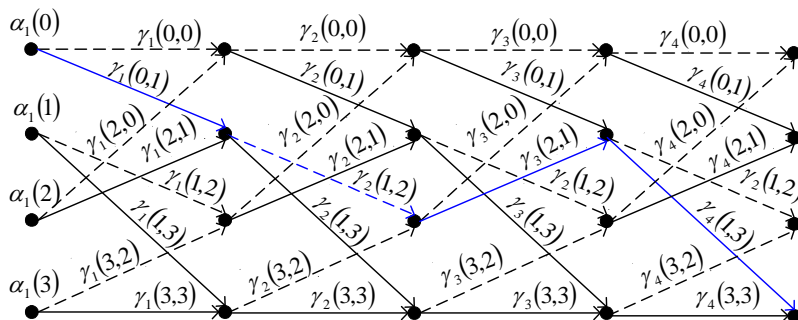


## TuEqu example (p=1)

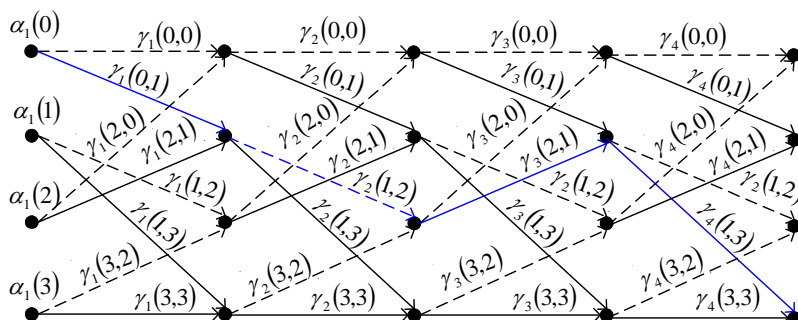


$$\gamma(s', s) = P(c_n^\pi) \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(r_n - v_n)^2}{2\sigma^2}\right)$$

## TuEqu example (p=1)



## TuEqu example (p=1)



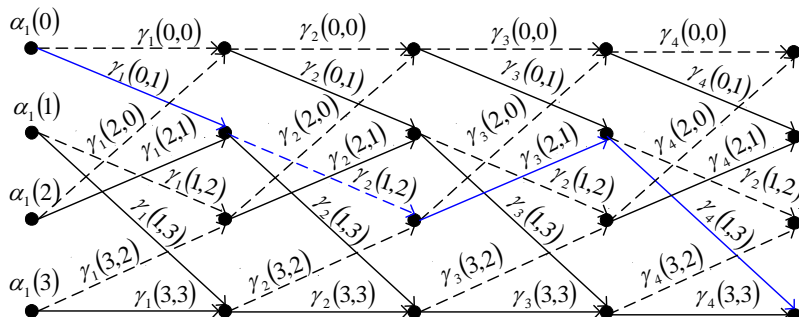
$$\alpha_2(0) = \alpha_1(0) \cdot \gamma_1(0,0) + \alpha_1(2) \cdot \gamma_1(2,0) = 1.0,1955 + 0 = 0,1955$$

$$\alpha_2(1) = \alpha_1(0) \cdot \gamma_1(0,1) + \alpha_1(2) \cdot \gamma_1(2,1) = 1.0,1970 + 0 = 0,1970$$

$$\alpha_2(2) = \alpha_1(1) \cdot \gamma_1(1,2) + \alpha_1(3) \cdot \gamma_1(3,2) = 0$$

$$\alpha_2(3) = \alpha_1(1) \cdot \gamma_1(1,3) + \alpha_1(3) \cdot \gamma_1(3,3) = 0$$

## TuEqu example (p=1)



$$\alpha_3(0) = \alpha_2(0) \cdot \gamma_2(0,0) + \alpha_2(2) \cdot \gamma_2(2,0) = 0,1955 \cdot 0,2152 + 0 = 0,0421$$

$$\alpha_3(1) = \alpha_2(0) \cdot \gamma_2(0,1) + \alpha_2(2) \cdot \gamma_2(2,1) = 0,1970 \cdot 0,1595 + 0 = 0,0312$$

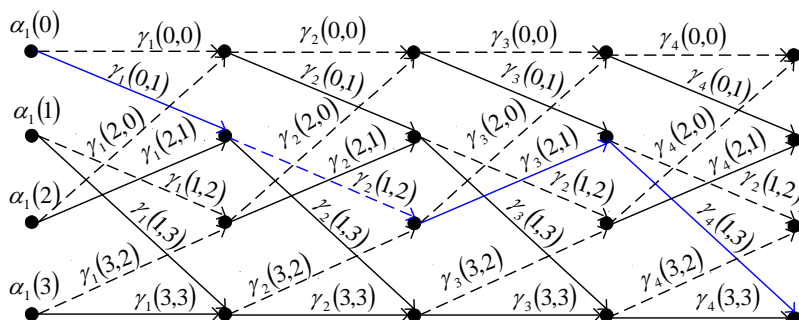
$$\alpha_3(2) = \alpha_2(1) \cdot \gamma_2(1,2) + \alpha_2(3) \cdot \gamma_2(3,2) = 0,1970 \cdot 0,0542 + 0 = 0,0106$$

$$\alpha_3(3) = \alpha_2(1) \cdot \gamma_2(1,3) + \alpha_2(3) \cdot \gamma_2(3,3) = 0,1970 \cdot 0,0084 + 0 = 0,0017$$

47

IWT 2004

## TuEqu example (p=1)



$$\alpha_4(0) = \alpha_3(0) \cdot \gamma_3(0,0) + \alpha_3(2) \cdot \gamma_3(2,0) = 0,0029$$

$$\alpha_4(1) = \alpha_3(0) \cdot \gamma_3(0,1) + \alpha_3(2) \cdot \gamma_3(2,1) = 0,0078$$

$$\alpha_4(2) = \alpha_3(1) \cdot \gamma_3(1,2) + \alpha_3(3) \cdot \gamma_3(3,2) = 0,0070$$

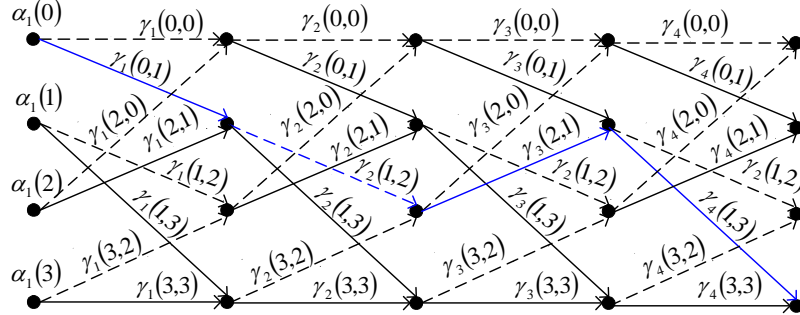
$$\alpha_4(3) = \alpha_3(1) \cdot \gamma_3(1,3) + \alpha_3(3) \cdot \gamma_3(3,3) = 0,0051$$

48

IWT 2004



## TuEqu example (p=1)



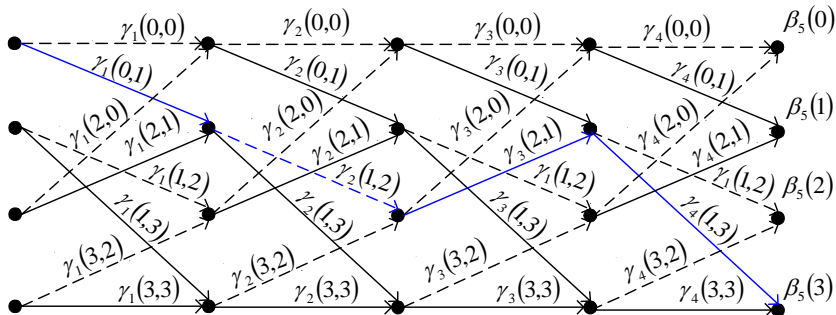
$$\alpha_5(0) = \alpha_4(0) \cdot \gamma_4(0,0) + \alpha_4(2) \cdot \gamma_4(2,0) = 0,0002$$

$$\alpha_5(1) = \alpha_4(0) \cdot \gamma_4(0,1) + \alpha_4(2) \cdot \gamma_4(2,1) = 0,0008$$

$$\alpha_5(2) = \alpha_4(1) \cdot \gamma_4(1,2) + \alpha_4(3) \cdot \gamma_4(3,2) = 0,0019$$

$$\alpha_5(3) = \alpha_4(1) \cdot \gamma_4(1,3) + \alpha_4(3) \cdot \gamma_4(3,3) = 0,0025$$

## TuEqu example (p=1)



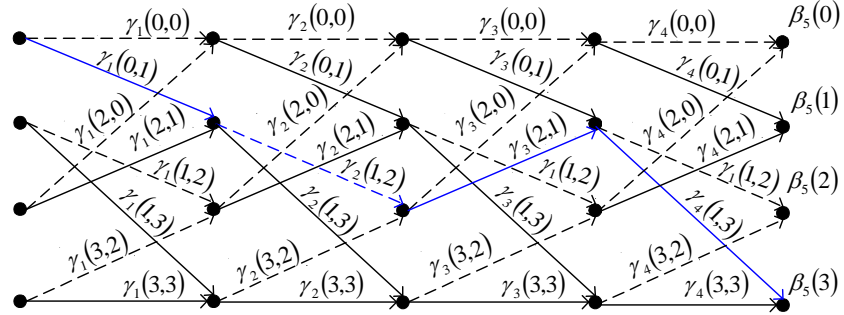
$$\beta_4(0) = \beta_5(0) \cdot \gamma_4(0,0) + \beta_5(1) \cdot \gamma_4(0,1) = 0,1 \cdot 10^{-9}$$

$$\beta_4(1) = \beta_5(2) \cdot \gamma_4(1,2) + \beta_5(3) \cdot \gamma_4(1,3) = 0,5 \cdot 10^{-9}$$

$$\beta_4(2) = \beta_5(0) \cdot \gamma_4(2,0) + \beta_5(1) \cdot \gamma_4(2,1) = 0,4 \cdot 10^{-9}$$

$$\beta_4(3) = \beta_5(2) \cdot \gamma_4(3,2) + \beta_5(3) \cdot \gamma_4(3,3) = 0,5 \cdot 10^{-9}$$

## TuEqu example (p=1)



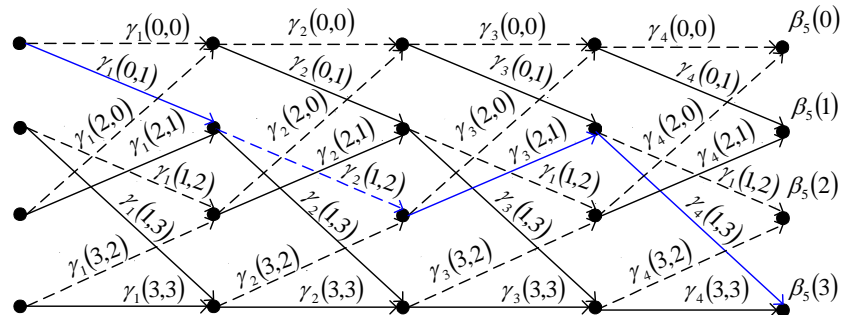
$$\beta_3(0) = \beta_4(0)\gamma_3(0,0) + \beta_4(1)\gamma_3(0,1) = 0,0.10^{-9}$$

$$\beta_3(1) = \beta_4(2)\gamma_3(1,2) + \beta_4(3)\gamma_3(1,3) = 0,2.10^{-9}$$

$$\beta_3(2) = \beta_4(0)\gamma_3(2,0) + \beta_4(1)\gamma_3(2,1) = 0,1.10^{-9}$$

$$\beta_3(3) = \beta_4(2)\gamma_3(3,2) + \beta_4(3)\gamma_3(3,3) = 0,1.10^{-9}$$

## TuEqu example (p=1)



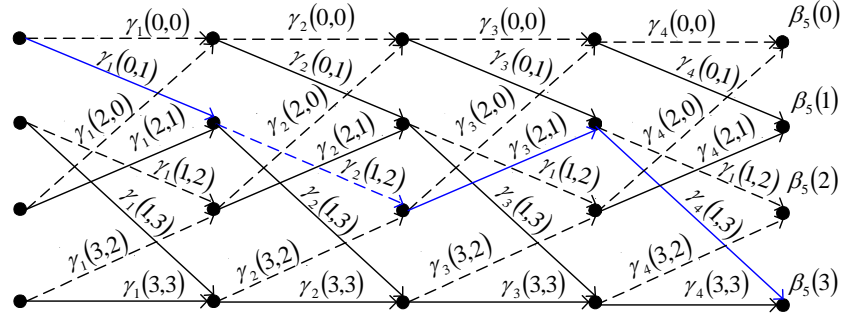
$$\beta_2(0) = \beta_3(0)\gamma_2(0,0) + \beta_3(1)\gamma_2(0,1) = 0,4.10^{-10}$$

$$\beta_2(1) = \beta_3(2)\gamma_2(1,2) + \beta_3(3)\gamma_2(1,3) = 0,1.10^{-10}$$

$$\beta_2(2) = \beta_3(0)\gamma_2(2,0) + \beta_3(1)\gamma_2(2,1) = 0,2.10^{-10}$$

$$\beta_2(3) = \beta_3(2)\gamma_2(3,2) + \beta_3(3)\gamma_2(3,3) = 0,0.10^{-10}$$

## TuEqu example (p=1)



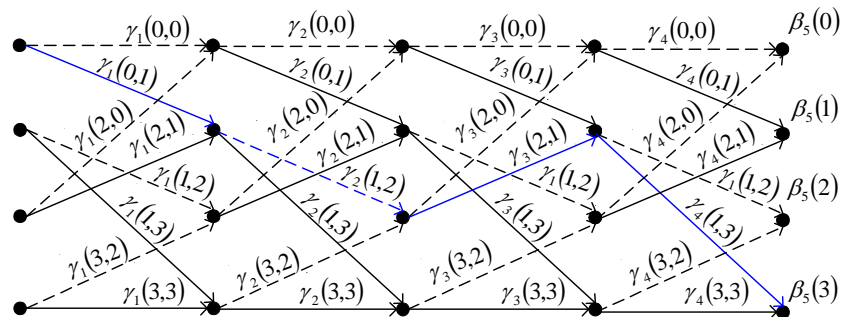
$$\beta_1(0) = \beta_2(0) \cdot \gamma_1(0,0) + \beta_2(1) \cdot \gamma_1(0,1) = 0,1 \cdot 10^{-10}$$

$$\beta_1(1) = \beta_2(2) \cdot \gamma_1(1,2) + \beta_2(3) \cdot \gamma_1(1,3) = 0,0 \cdot 10^{-10}$$

$$\beta_1(2) = \beta_2(0) \cdot \gamma_1(2,0) + \beta_2(1) \cdot \gamma_1(2,1) = 0,1 \cdot 10^{-10}$$

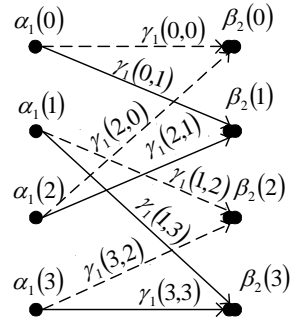
$$\beta_1(3) = \beta_2(2) \cdot \gamma_1(3,2) + \beta_2(3) \cdot \gamma_1(3,3) = 0,0 \cdot 10^{-10}$$

## TuEqu example (p=1)



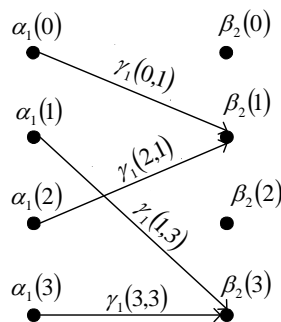
$$L^E(c_n^\pi | \mathbf{r}) = \ln \frac{\left( \sum_{c_n^\pi=+1} p(S_{n-1}, S_n, \mathbf{r}) \right)}{\left( \sum_{c_n^\pi=-1} p(S_{n-1}, S_n, \mathbf{r}) \right)} = \ln \frac{\left( \sum_{c_n^\pi=+1} \alpha_{n-1}(s') \gamma_n(s', s) \beta_n(s) \right)}{\left( \sum_{c_n^\pi=-1} \alpha_{n-1}(s') \gamma_n(s', s) \beta_n(s) \right)}$$

## TuEqu example (p=1)



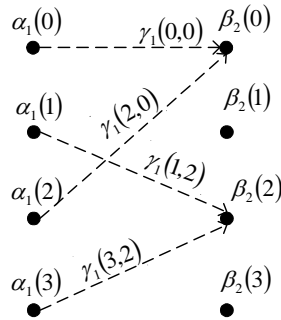
$$L^E(c_1 | \mathbf{r}) = \ln \frac{\left( \sum_{c_n^\pi = +1} p(S_{n-1}, S_n, \mathbf{r}) \right)}{\left( \sum_{c_n^\pi = -1} p(S_{n-1}, S_n, \mathbf{r}) \right)}$$

## TuEqu example (p=1)



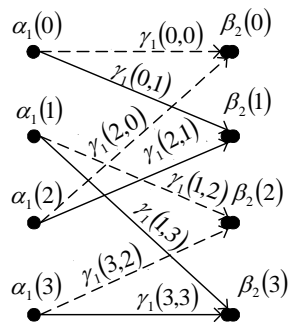
$$\sum_{c_n^\pi = +1} p(S_{n-1}, S_n, \mathbf{r}) = \alpha_1(0) \cdot \gamma_1(0,1) \cdot \beta_2(1) + \alpha_1(1) \cdot \gamma_1(1,3) \cdot \beta_2(3) \\ + \alpha_1(2) \cdot \gamma_1(2,1) \cdot \beta_2(1) + \alpha_1(3) \cdot \gamma_1(3,3) \cdot \beta_2(3)$$

## TuEqu example (p=1)



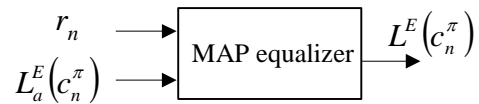
$$\sum_{c_n^\pi=-1} p(S_{n-1}, S_n, \mathbf{r}) = \alpha_1(0) \cdot \gamma_1(0,0) \cdot \beta_2(0) + \alpha_1(1) \cdot \gamma_1(1,2) \cdot \beta_2(2) \\ + \alpha_1(2) \cdot \gamma_1(2,0) \cdot \beta_2(0) + \alpha_1(3) \cdot \gamma_1(3,2) \cdot \beta_2(2)$$

## TuEqu example (p=1)



$$L^E(c_1^\pi | \mathbf{r}) = \ln \left( \frac{\sum_{c_n^\pi=+1} p(S_{n-1}, S_n, \mathbf{r})}{\sum_{c_n^\pi=-1} p(S_{n-1}, S_n, \mathbf{r})} \right) = -1,7504$$

## TuEqu example (p=1)



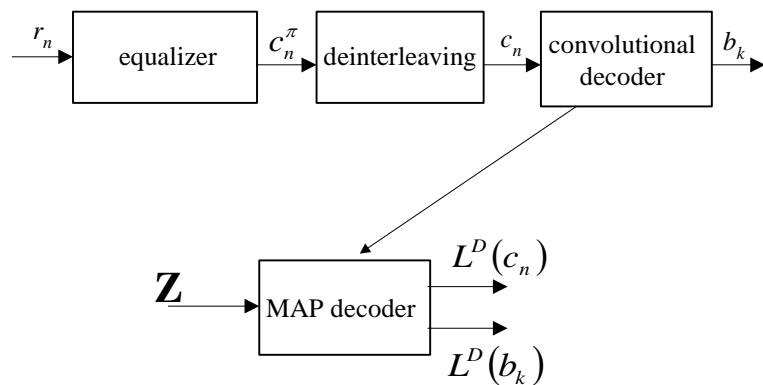
$$c_n = [1 \quad -1 \quad 1 \quad 1 \quad 1 \quad 1 \quad -1 \quad 1 \quad -1 \quad 1 \quad 1 \quad -1 \quad 1 \quad -1]$$

$$L^E(c_n^pi) = [-1,7504 \quad 0,2874 \quad 0,7274 \quad 1,7291\dots]$$

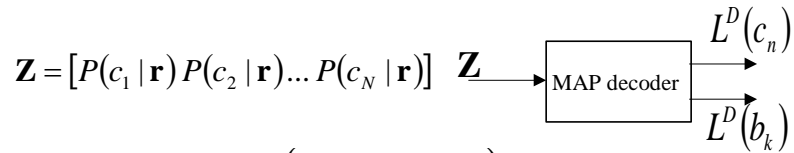
leads to wrong decisions



## TuEqu example (p=1)



## TuEqu example (p=1)



$$P(c_n | \mathbf{r}) \cong \frac{\exp(c \cdot L_{ext}^E(c_n | \mathbf{r}))}{1 + \exp(L_{ext}^E(c_n | \mathbf{r}))} \quad c \in \{0, 1\}$$

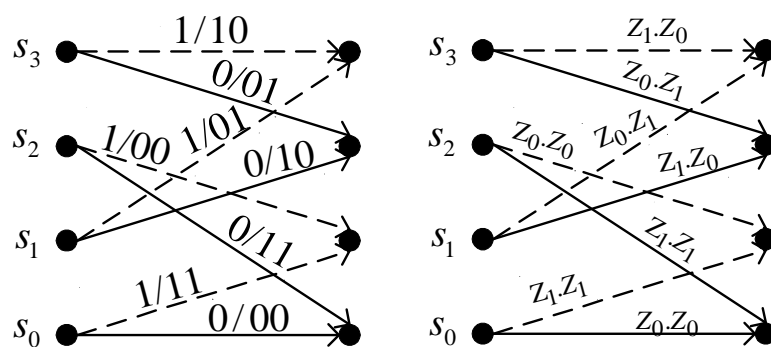
$$L^E(c_n) = [-1,7504 \quad 4,4354 \quad -0,9099 \quad 3,5313 \dots]$$

$$\mathbf{Z}(c_n = 1) = [0,1480 \quad 0,9883 \quad 0,2870 \quad 0,9716 \dots]$$

$$\mathbf{Z}(c_n = 0) = [0,8520 \quad 0,0117 \quad 0,7130 \quad 0,0284 \dots]$$



## TuEqu example (p=1)



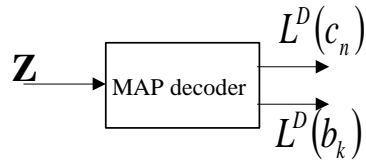
$$\mathbf{Z} = [P(c_1 | \mathbf{r}) P(c_2 | \mathbf{r}) \dots P(c_N | \mathbf{r})]$$

$$\gamma(s_i, s_j) = P(b_k) P(c_1 = c_{1,i,j} | \mathbf{r}) P(c_2 = c_{2,i,j} | \mathbf{r})$$

there is no a priori information of the information bits



## TuEqu example (p=1)



$$b_k = [1 \ 1 \ 0 \ 1 \ 0 \ 0 \ 1 \ 0]$$

Hard decisions of the information bits :

$$\hat{b}_k = [1 \ 1 \ 0 \ 0 \ 1 \ 0 \ 0 \ 1]$$

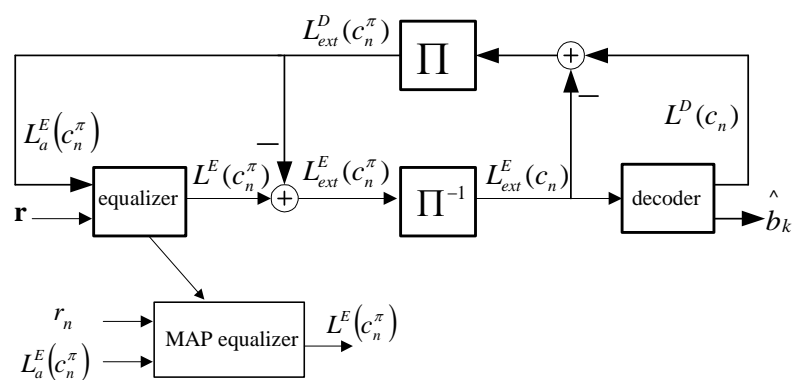
$$c_n = [1 \ 1 \ -1 \ 1 \ -1 \ 1 \ -1 \ -1 \ 1 \ -1 \ 1 \ -1 \ 1 \ 1 \ 1 \ -1]$$

Hard decisions of the coded bits :

$$\hat{c}_n = [1 \ 1 \ -1 \ 1 \ -1 \ 1 \ -1 \ 1 \ 1 \ 1 \ -1 \ 1 \ 1 \ 1 \ 1 \ 1]$$



## TuEqu example (p=2)



$$\gamma(s', s) = \frac{\exp(c \cdot L_{ext}^D(c_n^\pi))}{1 + \exp(L_{ext}^D(c_n^\pi))} \cdot \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-(r_n - v_n)^2 / 2\sigma^2)$$



## TuEqu example (p=2)

$$p = 1$$

$$c_n^\pi = [1 \quad -1 \quad 1 \quad 1 \quad 1 \quad 1 \quad -1 \quad 1 \quad -1 \quad -1 \quad 1 \quad 1 \quad 1 \quad -1 \quad 1 \quad -1]$$

$$L^E(c_n^\pi) = [-1,7504 \quad 0,2874 \quad 0,7274 \quad 1,7291\dots]$$

leads to wrong decisions

$$p = 2$$

$$c_n^\pi = [1 \quad -1 \quad 1 \quad 1 \quad 1 \quad 1 \quad -1 \quad 1 \quad -1 \quad -1 \quad 1 \quad 1 \quad 1 \quad -1 \quad 1 \quad -1]$$

$$L^E(c_n^\pi) = [3,9617 \quad -4,7377 \quad 2,0979 \quad 1,8811\dots]$$

errors corrected



## TuEqu example (p=2)

$$\mathbf{Z} \equiv [P(c_1 | \mathbf{r}) P(c_2 | \mathbf{r}) \dots P(c_N | \mathbf{r})] \quad \mathbf{Z} \rightarrow \begin{array}{|c|} \hline \text{MAP decoder} \\ \hline \end{array} \begin{array}{l} L^D(c_n) \\ L^D(b_k) \end{array}$$

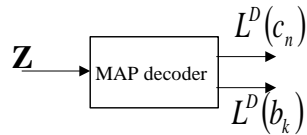
$$P(c_n | \mathbf{r}) \cong \frac{\exp(c_n \cdot L_{ext}^E(c_n | \mathbf{r}))}{1 + \exp(L_{ext}^E(c_n | \mathbf{r}))} \quad c \in \{0,1\}$$

$$L^E(c_n) = [-0,9085 \quad 4,2859 \quad -1,3199 \quad 3,9053\dots]$$

$$Z(c_n = 1) = [0,2873 \quad 0,9864 \quad 0,2108 \quad 0,9803\dots]$$

$$Z(c_n = 0) = [0,7127 \quad 0,0136 \quad 0,7892 \quad 0,0197\dots]$$

## TuEqu example (p=2)



$$b_k = [1 \ 1 \ 0 \ 1 \ 0 \ 0 \ 1 \ 0]$$

Hard decisions of the information bits :

$$\hat{b}_k = [1 \ 1 \ 0 \ 1 \ 0 \ 0 \ 0 \ 1]$$

$$c_n = [1 \ 1 \ -1 \ 1 \ -1 \ 1 \ -1 \ -1 \ 1 \ -1 \ 1 \ -1 \ 1 \ 1 \ 1 \ -1]$$

Hard decisions of the coded bits :

$$\hat{c}_n = [1 \ 1 \ -1 \ 1 \ -1 \ 1 \ -1 \ -1 \ 1 \ -1 \ 1 \ -1 \ 1 \ 1 \ 1 \ 1]$$

## TuEqu example (p=2)

$$p = 1$$

Hard decisions of the information bits :

$$\hat{b}_k = [1 \ 1 \ 0 \ 0 \ 1 \ 0 \ 0 \ 1]$$

Hard decisions of the coded bits :

$$\hat{c}_n = [1 \ 1 \ -1 \ 1 \ -1 \ 1 \ -1 \ 1 \ 1 \ 1 \ -1 \ 1 \ 1 \ 1 \ 1 \ 1]$$

$$p = 2$$

Hard decisions of the information bits :

$$\hat{b}_k = [1 \ 1 \ 0 \ 1 \ 0 \ 0 \ 0 \ 1]$$

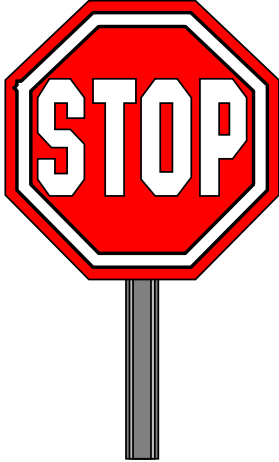
Hard decisions of the coded bits :


$$\hat{c}_n = [1 \ 1 \ -1 \ 1 \ -1 \ 1 \ -1 \ -1 \ 1 \ -1 \ 1 \ -1 \ 1 \ 1 \ 1 \ 1]$$



Turbo Equalization

## Questions???






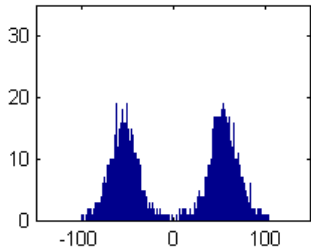
IWT 2004
69

Turbo Equalization

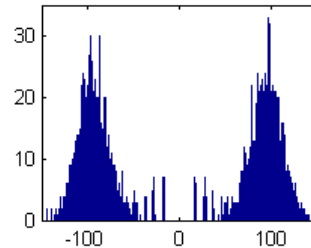
## Evolution of the LLR's



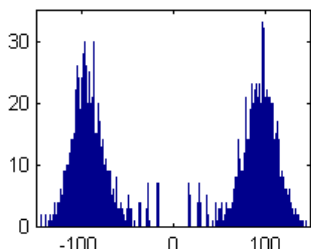
without interaction



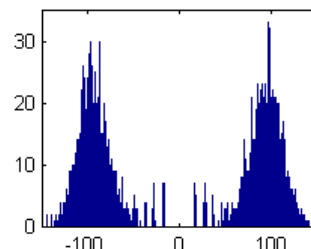
first interaction



second interaction

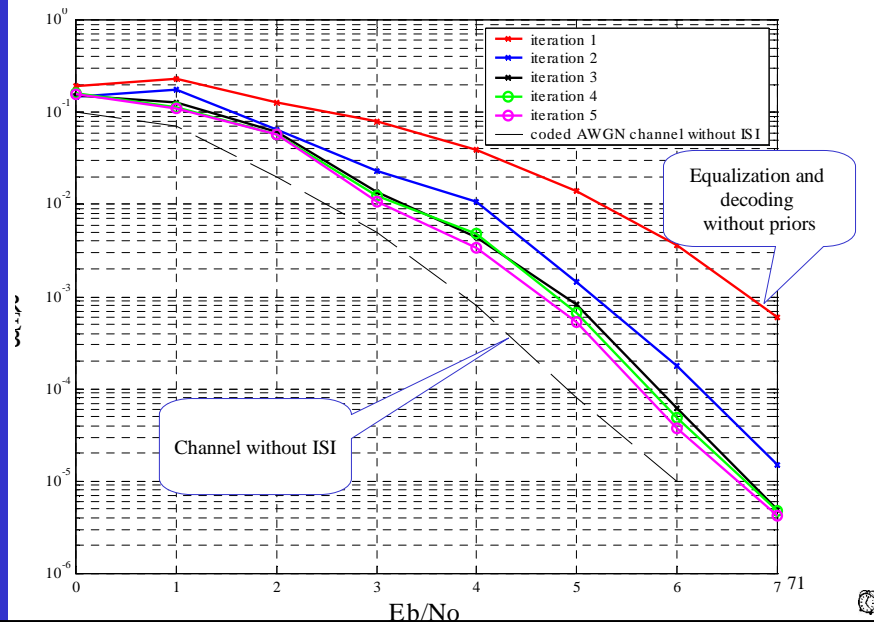


fourth interaction



IWT 2004
70

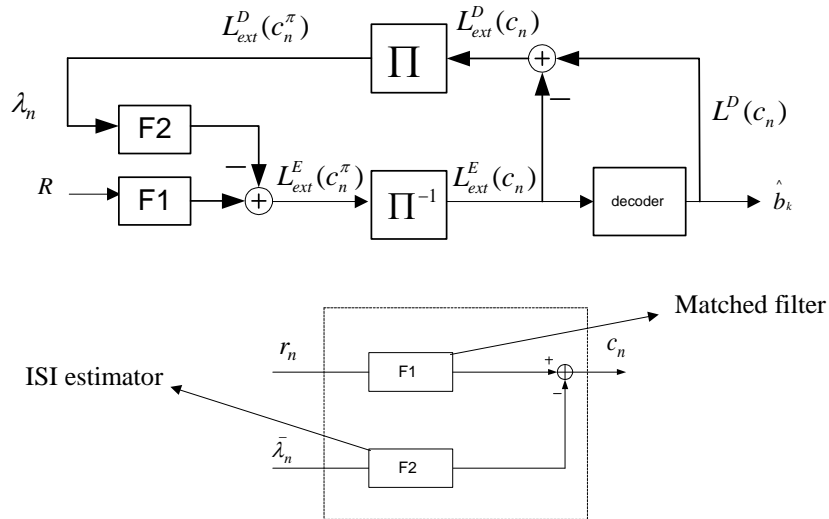
## Results



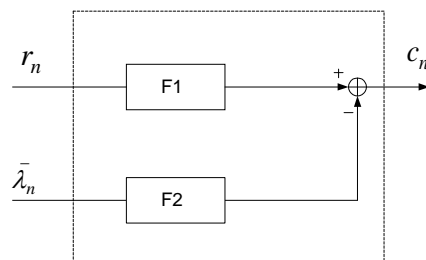
## TuEqu using MAP

- The MAP algorithm applied in turbo equalization is adequate to low spectral efficiency modulations and channels exhibiting a low delay spread.
- In 1997, Glavieux proposed an *Interference Canceller* in the Turbo Equalizer for channels with strong delay spread and high order modulations.

## Turbo Equalization with IC

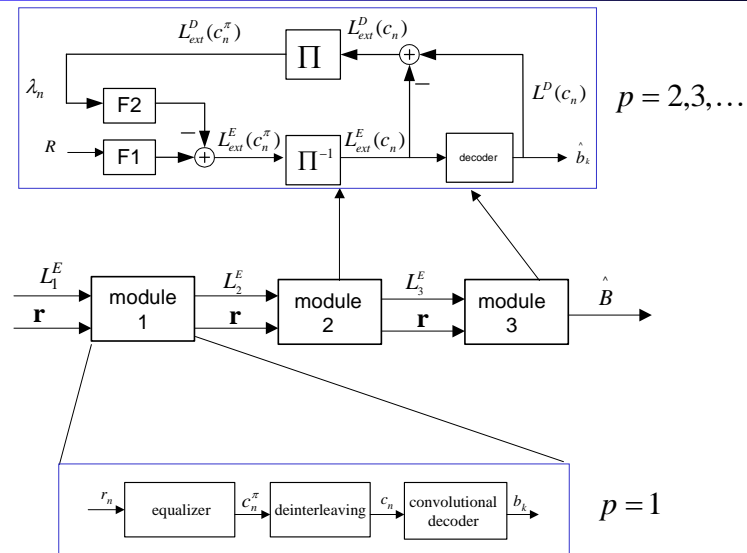


## Turbo Equalization with IC



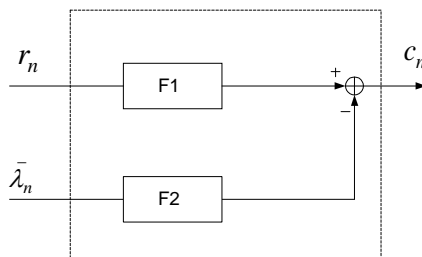
The input of the filter F2 is :

$$\begin{aligned}\bar{\lambda}_n &= E\{c_k\} = P(c_n = +1) \cdot 1 + P(c_n = -1) \cdot (-1) \\ &= \frac{\exp(L(c_n))}{1 + \exp(L(c_n))} + \frac{-1}{1 + \exp(L(c_n))} = \tanh\left(\frac{L_{ext}^D(c_k)}{2}\right)\end{aligned}$$



IWT 2004

75



For each stage, the equalizer is updated according to the mean - square - error (MSE) criterion [Laot]:

$$MSE = E\{|c_n - \lambda_n|^2\}$$

$$W_{k+1} = W_k - \mu \cdot R(s_n - \hat{c}_n)$$

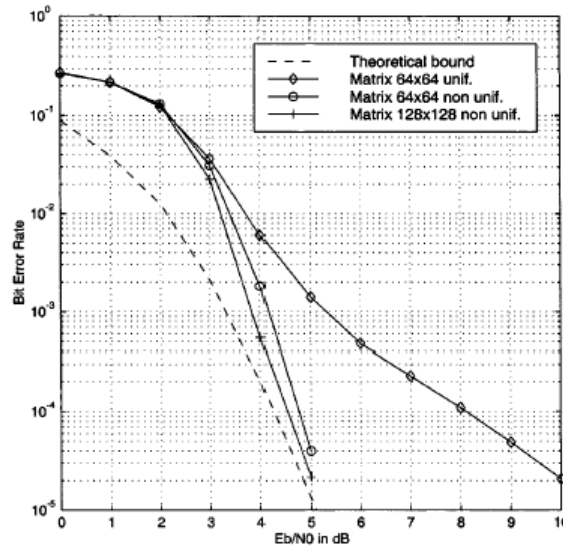
$$D_{k+1} = D_k + \mu.R(s_n - \hat{c}_n)$$

IWT 2004

76



## Results [Laot]



IWT 2004

77

## TuEq, other approaches

- Turbo equalization using block codes
- Turbo equalization using turbo codes
- Turbo equalization using joint channel estimation and MAP equalization (BCJR).
- Turbo equalization applied in multi-user detection of CDMA systems.

IWT 2004

78

## Main references

- C. Douillard, M. Jezequel, C. Berrou, A. Picart, P. Didier, and A. Glavieux. **Iterative Correction of Intersymbol Interference: Turbo Equalization.** European Trans. On Telecomm., vol. 6, pp. 507–511, Sep-Oct 1995.
- L. Hanzo, T. H. Liew, and B. L. Yeap. **Turbo Coding, Turbo equalization and Space-Time Coding for Transmission Over Fading Channels.** John Wiley and Sons, Inc 2002
- G. Bauch, H. Khorram and J. Hagenauer. **Iterative Equalization and Decoding in Mobile Communication Systems.** 2<sup>nd</sup> EPMCC'97 and 3<sup>rd</sup> ITG-Fachtagung Telecomm, Mobile Kommunikation, Bonn, Germany, Oct. 1997.

## Main references

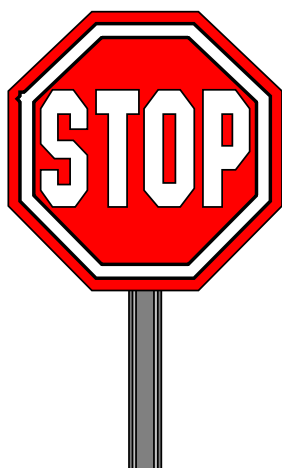
- A. Glavieux, C. Laot, and J. Labat. **Turbo Equalization Over a Frequency Selective Channel.** Proc. Of the Intern. Symposium on Turbo codes, Brest, France, pp. 96–102, September 1997.
- C. Laot, A. Glavieux and J. Labat. **Turbo Equalization: Adaptive Equalization and Channel Decoding Jointly Optimized.** IEE Journal on Selected Areas in Communications, vol.19, n°9, september,2001
- T. Michael., Koetter. Ralf., A.. Singer. **Turbo Equalization.** IEEE Signal Processing Magazine, Feb 2003



## Questions???

**Inatel**  
Instituto Nacional de Telecomunicações

Turbo Equalization



IWT 2004

81