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## 7.1 Turbo Codes

### 7.1.1 Shannon Limit on Performance

- The capacity of an AWGN channel is given by

$$C = W \log_2 ( 1 + S / N )$$

where  $W$  is the bandwidth of the channel in Hz ,  $S$  is the average power of the signal and  $N$  is the noise power.

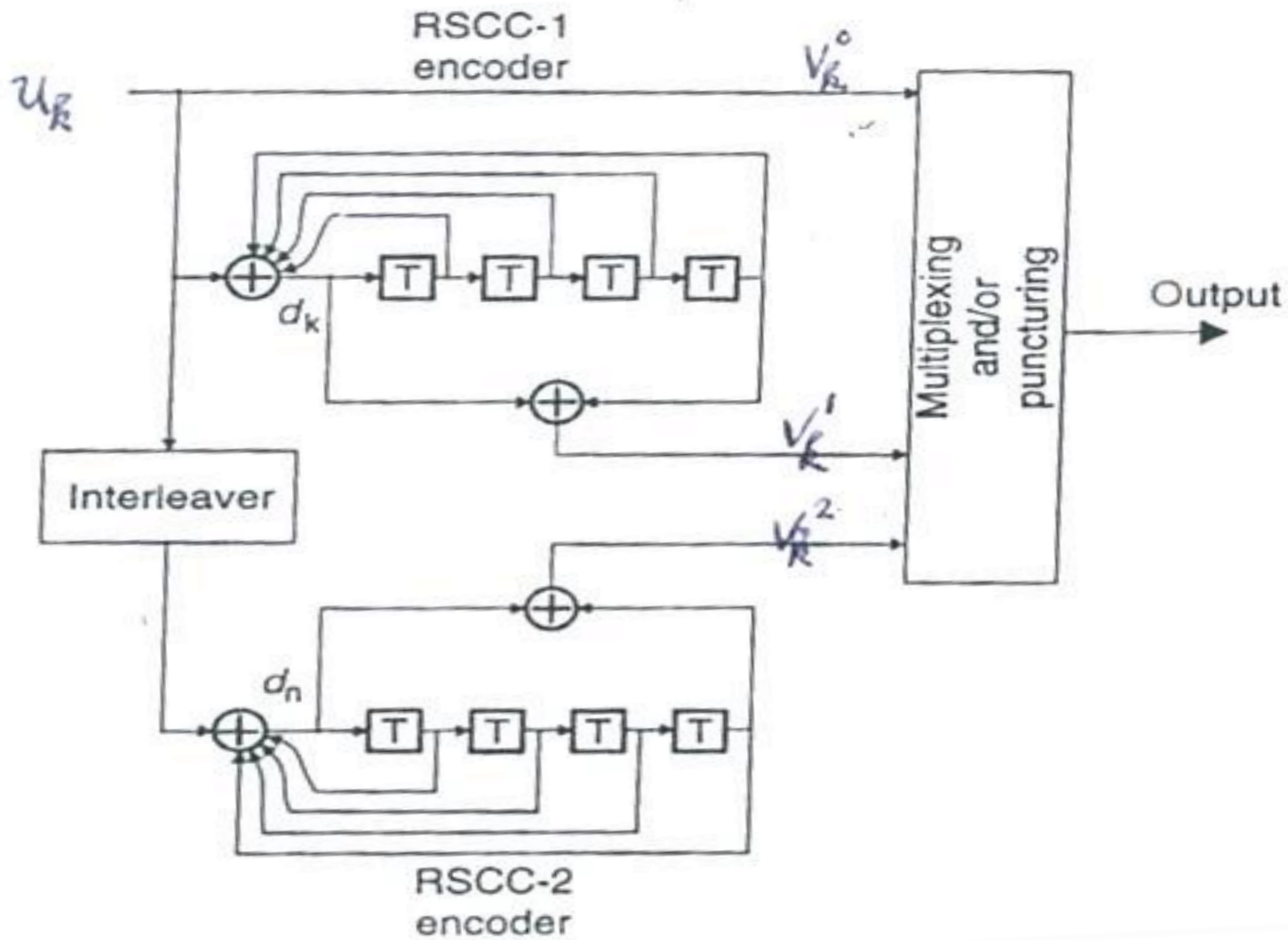
- Shannon bound
- In the limit as the signal is allowed to occupy an infinity amount of bandwidth, one obtains the Shannon bound

$$E_b / N_0 = - 1.59 \text{ dB}$$

for reliable transmission.

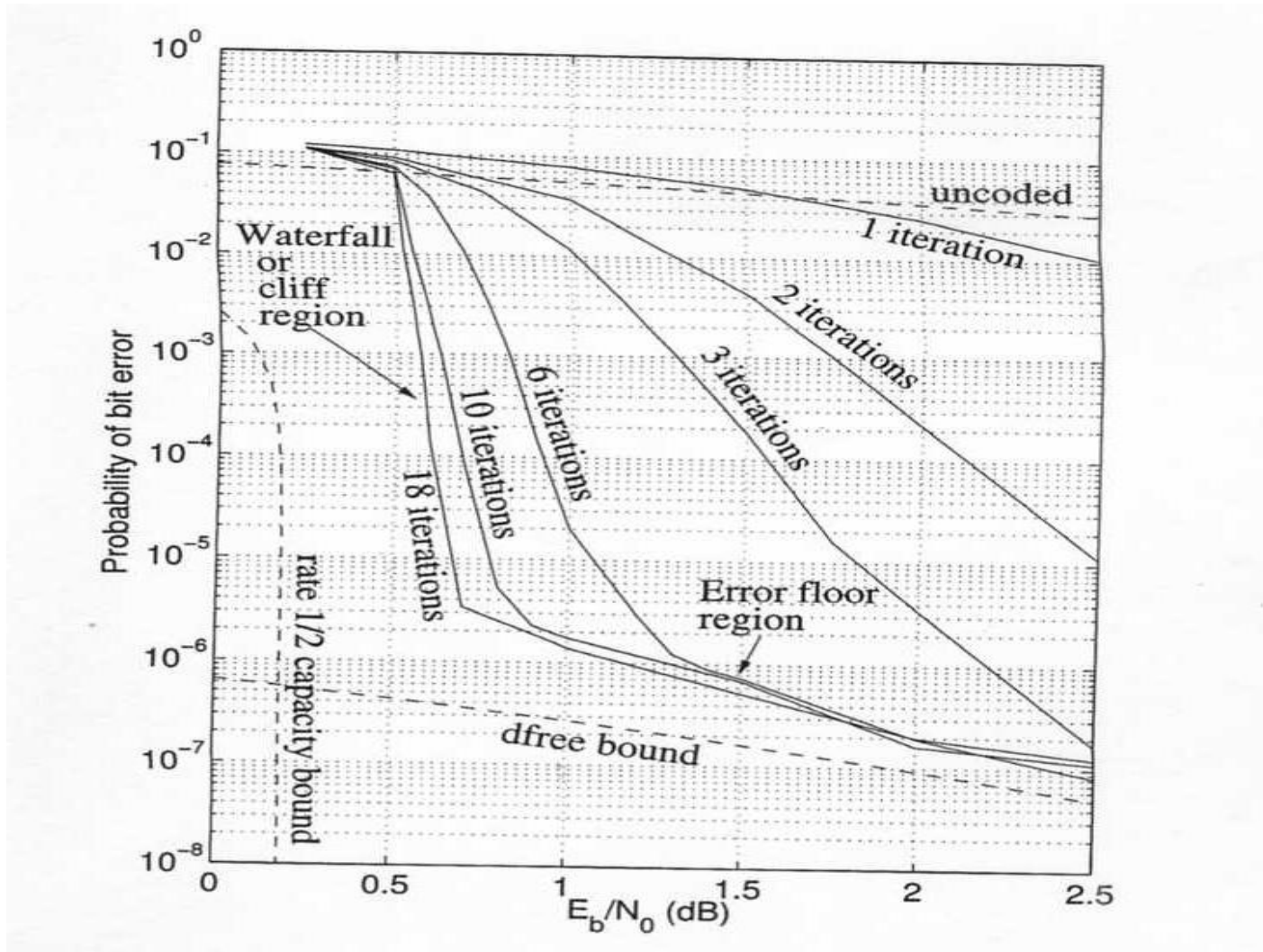
- **In 1948, Shannon defined the concept of channel capacity. He shown that, as long as the rate at which information is transmitted is less than the channel capacity, there exists error control codes that can provide arbitrarily high levels of reliability at the receiver output**
- **The 1993 paper by C. Berrou, A. Glavieux, and P. Thitimasjshima entitled “Near Shannon Limit Error Correcting Coding and Decoding : Turbo Codes” has brought us within a hair’s breadth of achieving Shannon’s promise. This paper was presented at 1993 IEEE International Conference on Communications in Geneva.**
- **In their presentation, Berrou et al claimed that a combination of **parallel concatenation** and **iterative decoding** can provide reliable communication at a SNR that is within a few tenth of a dB of the Shannon limit.**

# Turbo code encoder ( Berrou *et al* , 1993)

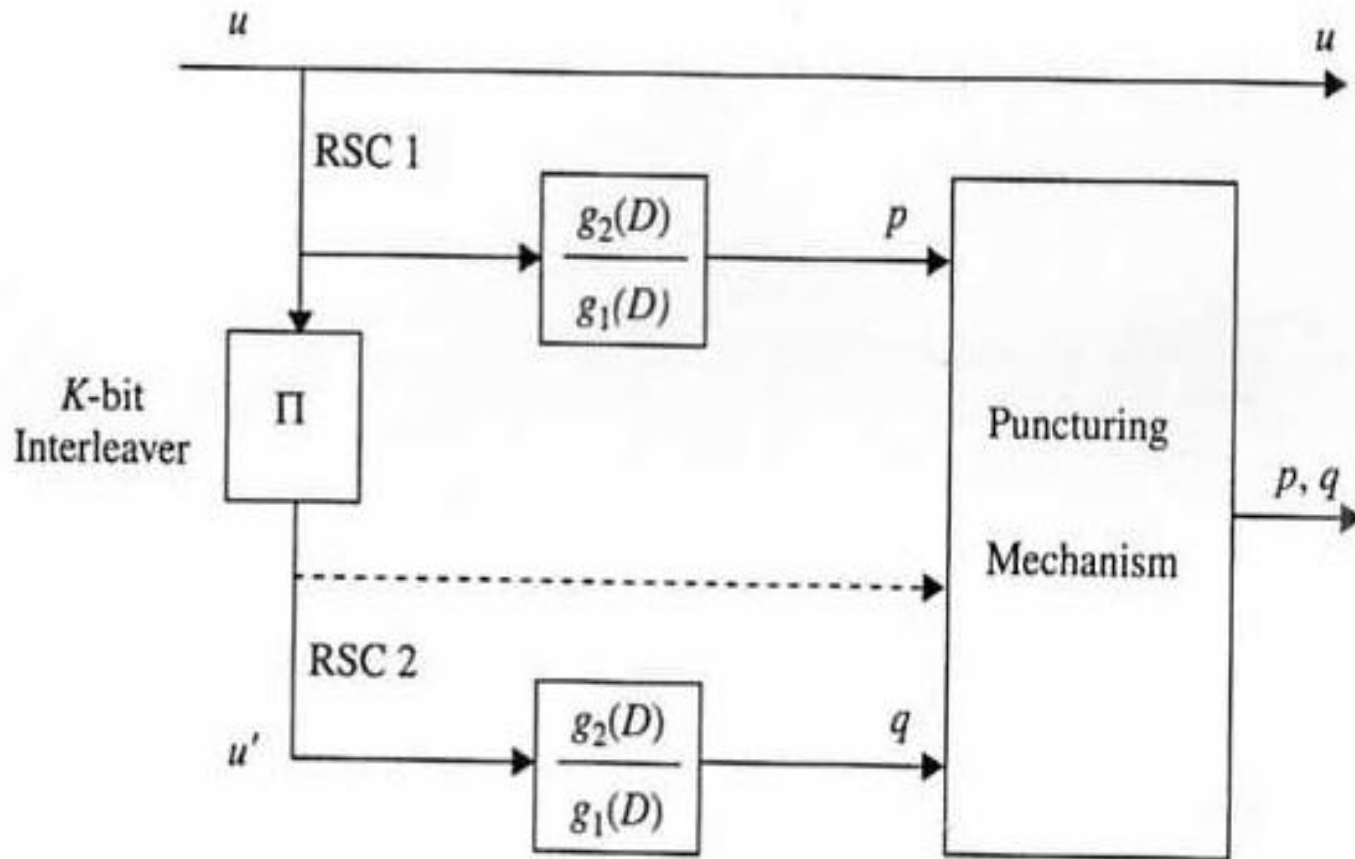


# Decoding result of (37,21 ,65536) turbo code

Note : Octal numbers 37 =11 111 , 21 = 10001 .Block length N =65536



## Standard structure for turbo code encoder



- **One key to the effectiveness of turbo coding systems is the interleaver.**
- **The interleaver allows the constituent decoders to generate separate *estimates* of the *a posteriori probability (APP)* for a given information symbol based on data sources that are not highly corrected.**
- **The pseudorandom interleaver in this circuit is used to permute the input bits in such a manner that the two encoders operate on the same set of input bits, but with different input sequence to the encoders.**



## 7.1.3 Decoding of Turbo Codes

- The iterative decoder uses a **soft-in/soft-out** maximum *a posteriori* probability (MAP) decoding algorithm.
- This algorithm was first applied to convolutional codes by **BCJR algorithm** , introduced by Bahl, Cocke, Jelinek, and Raviv in 1974.
- The BCJR algorithm differs from the Viterbi algorithm in the sense that it produces **soft outputs** . The **soft output** weights the confidence or log-likelihood of each bit estimate.
- The BCJR algorithm attempts to minimize the bit-error-rate by estimating the **a posteriori probability (APP)** of the **individual bits** of the codeword, rather than the ML estimate of the transmitted **codeword** .

- For encoder given in Fig.8.4, there are two elementary decoders that are interconnected as shown in Fig. 8.xx
    - The BCJR algorithm is employed in each decoder.
- The data  $(r^{(0)}, r^{(1)})$  associated with the first encoder are fed to Decoder 1. This decoder initially uses uniform priors on the transmitted bits and produces probabilities of the bits conditioned on the observed data. These probabilities are called the **extrinsic** probabilities. The output probabilities of Decoder 1 are interleaved and passed to Decoder 2, where they are used as “prior” probabilities in the decoder, along with the data associated the second encoder, which is  $r^{(0)}$  (interleaved) and  $r^{(2)}$ .

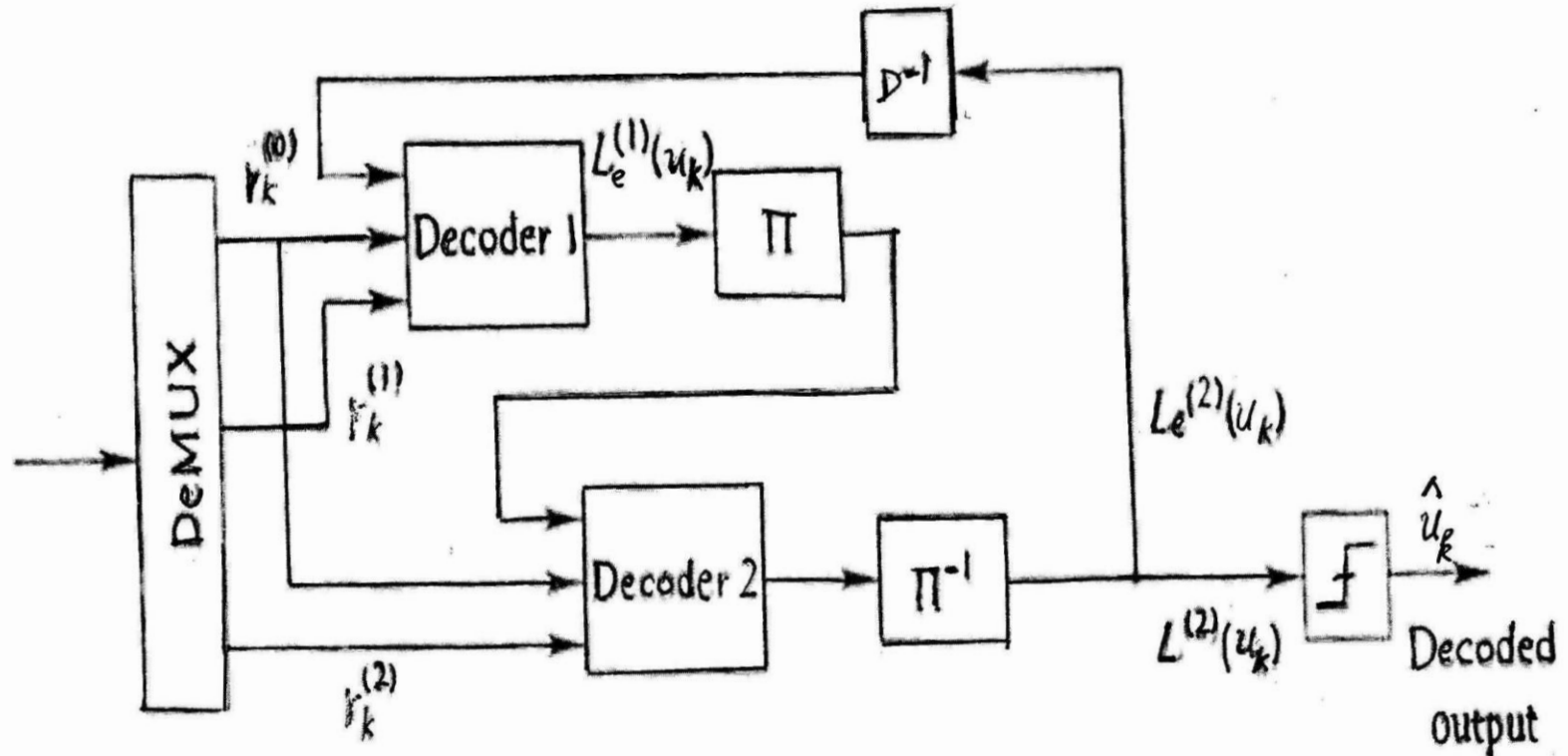
- The extrinsic output probabilities of Decoder II are deinterleaved and passed back to become prior probabilities to Decoder 1.

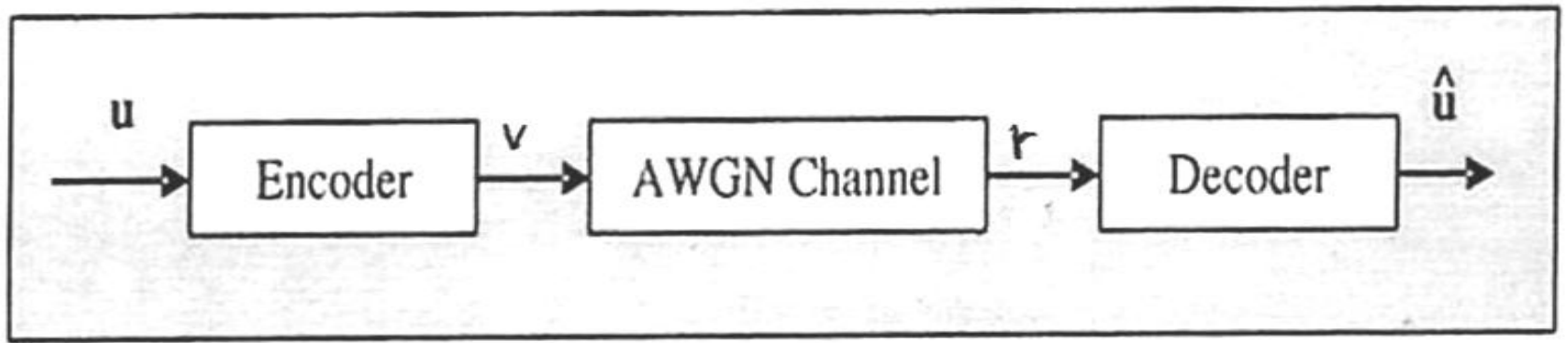
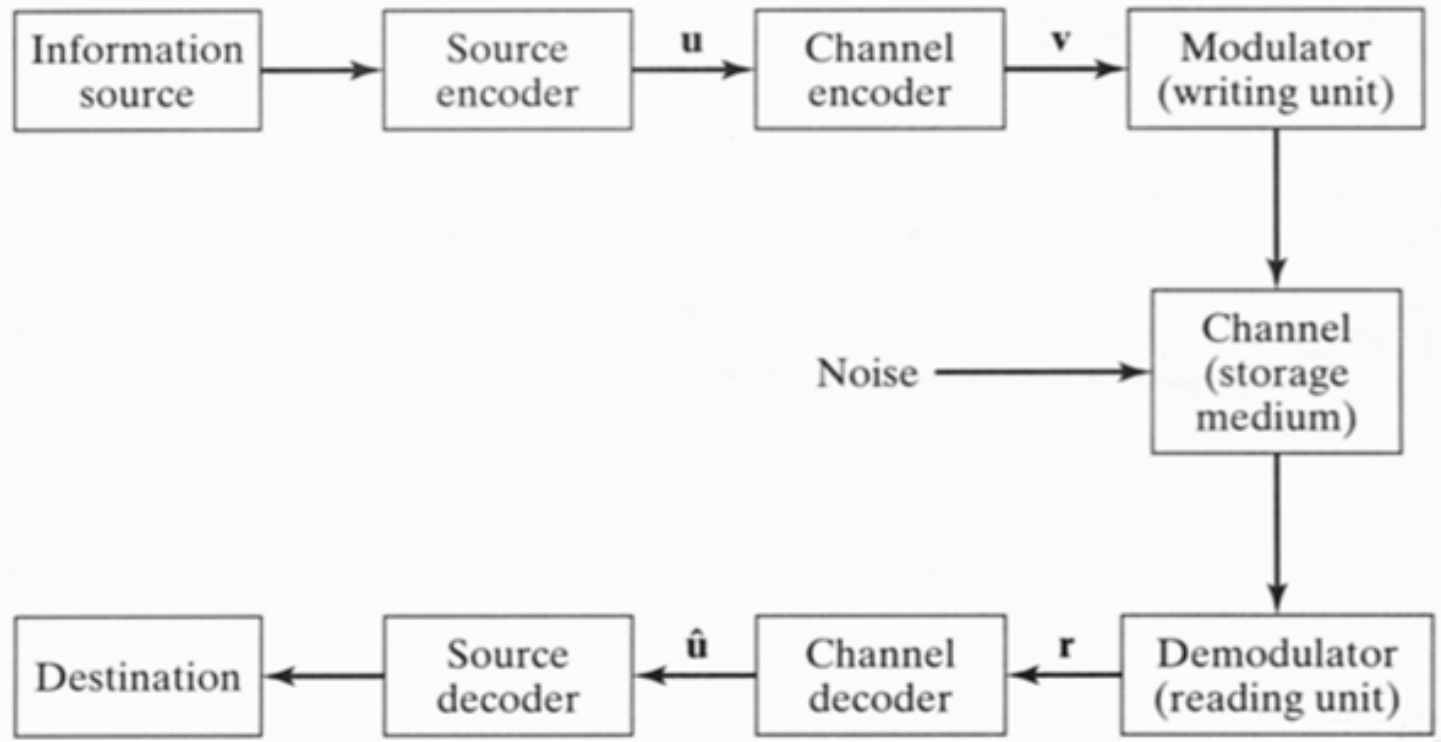
The process of passing probability information back and forth continues until the decoder determines (somehow) that the process has converged, or until some maximum number of iteration has reached.

- When iterative decoding is employed (e.g. turbo decoding), and the *a posteriori* probabilities of the information bits change from iteration to iteration, a MAP decoder gives the best performance.

The term *turbo* in the turbo coding has more to do with decoding than encoding. Indeed, it is successive feedback of extrinsic information from the SISO decoders in the iterative decoding process that mimics the feedback of exhaust gasses in a turbocharged engine.

# A simplified Turbo decoder structure





## 7.2 BCJR Algorithm

### 7.2.1 Log-likelihood Ratio

- We consider transmitting message over a binary- input continuous output memoryless channel . The input  $u_k$  equals to  $+1$  or  $-1$ .

- The **log-likelihood ratio (LLR)** of a transmitted symbol  $u_k$ , with the received sequence  $r$ , is defined as

$$L(u_k) = \ln [ p(u_k = +1 | r) / p(u_k = -1 | r) ] \quad (7.1)$$

$L(u_k)$  is also denoted as ***a posteriori probability (APP)***

**L-value** .

- The ***a priori*** L-value of an **information bit**  $u_k$  is defined as

$$L_a(u_k) = \ln [ p(u_k = +1) / p(u_k = -1) ] \quad (7.2)$$

- An L-value can be interpreted as a measure of reliability for a binary random variable .

For example, assuming that the *a priori* probabilities of the code bits  $u$  are equally likely , that is,

$p(u=1) = p(u = -1 ) = 1/2$  , then, using Bayes' rule , we have

$$\begin{aligned} L(r) &= \ln [ p(r | u= + 1) / p(r | u = - 1) ] \\ &= \ln [ p( u = + 1 | r ) / p( u = - 1 | r ) ] \quad (7.3) \end{aligned}$$

From this equation, we see that given the received symbol  $r$  , a large positive value of  $L(r)$  indicates a high reliability that  $u= +1$  , a large negative value of  $L(r)$  indicates a high reliability that  $u = -1$  .

## 7.2.2 BCJR Algorithm

- Here we describe the BCJR algorithm for the case of rate  $R = 1/n$  convolutional codes used on a binary-input continuous-output AWGN channel and on a discrete memoryless channel (DMC).

The decoder inputs are the received sequence  $r$  and the *a priori* L-values of the **information** bits  $L_a(u_k)$ ,  $k = 0, 1, 2, \dots, K-1$ .

The algorithm calculates the APP L-values

$$L(u_k) = \ln [ p(u_k = +1 | r) / p(u_k = -1 | r) ] \quad (7.4)$$

of each information bit.

The decoder output is given by

$$u_k^{\wedge} = \begin{matrix} +1 & \text{if } L(u_k) > 0 \\ -1 & \text{if } L(u_k) < 0 \end{matrix}, \quad k = 0, 1, 2, \dots, K-1. \quad (7.5)$$



- The APP value  $p(u_k = +1 | r)$  can be rewritten as

$$p(u_k = +1 | r) = p(u_k = +1, r) / p(r)$$

$$= \sum_{U_+} p(s_k = s', s_{k+1} = s, r) / p(r) \quad (7.6)$$

where  $U_+$  is the set of transition from state  $s_k$  to the state  $s_{k+1}$  that can occur **if the input bit  $u_k = +1$** .

Similarly, we can rewrite  $p(u_k = -1 | r)$  as

$$p(u_k = -1 | r) = p(u_k = -1, r) / p(r)$$

$$= \sum_{U_-} p(s_k = s', s_{k+1} = s, r) / p(r) \quad (7.7)$$

where  $U_-$  is the set of transition from state  $s_k$  to the state  $s_{k+1}$  that can occur **if the input bit  $u_k = -1$** .

■ The APP L-value can be expressed as

$$L(u_k) = \ln \left\{ \frac{\sum_{U^+} p(s_k = s', s_{k+1} = s, r)}{\sum_{U^-} p(s_k = s', s_{k+1} = s, r)} \right\} \quad (7.8)$$

■ Now we will show how the joint pdf  $p(s', s, r)$  can be evaluated **recursively**.

Note that  $p(s', s, r) = p(s_k = s', s_{k+1} = s, r)$ .

The convolutional code introduces a **Markov** property into the probability structure:

Knowledge of the state at time  $t+1$  renders irrelevant knowledge of the state at time  $t$  or previous time.

**The observation  $\mathbf{r}$  is divided into three portions :  $\mathbf{r}_{t < k}$  ,  $\mathbf{r}_k$  ,  $\mathbf{r}_{t > k}$  ,** where  $\mathbf{r}_{t < k}$  represents the portion of the received sequence before time  $k$  , and  $\mathbf{r}_{t > k}$  represents the portion of the received sequence  $y$  after time  $k$  .

$$\mathbf{r} = r_1 r_2 \dots r_{k-1} r_k r_{k+1} \dots r_N = \mathbf{r}_{t < k} \mathbf{r}_k \mathbf{r}_{t > k} \quad (7.9)$$

- We then have  $p(s', s, r) = p(s', s, r_{t < k}, r_k, r_{t > k})$  and applying the Bayes's rule we obtain

$$\begin{aligned}
 p(s', s, r) &= p(r_{t > k} \mid s', s, r_{t < k}, r_k) p(s', s, r_{t < k}, r_k) \\
 &= p(r_{t > k} \mid s', s, r_{t < k}, r_k) p(s, r_t \mid s', r_{t < k}) P(s', r_{t < k}) \\
 &= p(r_{t > k} \mid s) P(s, r_k \mid s') p(s', r_{t < k}) \quad (7.10)
 \end{aligned}$$

where the last equality follows from the fact that the probability of the received branch at time  $k$  depends only on the state and input bit at time  $k$ .

- Defining

$$\alpha_k(s') \equiv p(s', r_{<k}) \quad (7.11)$$

$$\gamma_k(s', s) \equiv p(s, r_k \mid s') \quad (7.12)$$

$$\beta_{k+1}(s) \equiv p(r_{t > k} \mid s) \quad (7.13)$$

we then can write  $P(s', s, r)$  by the equation

$$p(s', s, r) = \alpha_k(s') \gamma_k(s', s) \beta_{k+1}(s) \quad (7.14)$$

- **Forward Recursion**

**We can now rewrite  $\alpha_k(s)$  as**

$$\begin{aligned} \alpha_{k+1}(s) &\equiv p(s, \mathbf{r}_{t < k+1}) = \sum_{s'} p(s', s, \mathbf{r}_{t < k}, \mathbf{r}_k) \\ &= \sum_{s'} p(s, \mathbf{r}_k \mid s', \mathbf{r}_{t < k}) p(s', \mathbf{r}_{t < k}) \\ &= \sum_{s'} p(s, \mathbf{r}_k \mid s') p(s', \mathbf{r}_{t < k}) \\ &= \sum_{s'} \alpha_k(s') \gamma_k(s', s) \end{aligned} \tag{7.15}$$

**where the summation is taken over all states at time  $k$ .**

**Thus, once the  $\gamma_k(s', s)$  values are known, the  $\alpha_{k+1}(s)$  can be calculated recursively.**

- Similarly, we can write the expression for the probability  $\beta_{k-1}(s')$  as

$$\beta_k(s') = \sum_s \beta_{k+1}(s) \gamma_k(s', s) \quad (7.16)$$

where *the summation is taken over* all states at time  $k+1$ , and we can compute a **backward metric**  $\beta_k(s')$  for each state  $s'$  at time  $k$  using the **backward recursion** (7.16).

- The forward recursion begins at time  $k=0$  with the initial condition

$$\alpha_0(s) = \begin{cases} 1, & s = 0 \\ 0, & s \neq 0 \end{cases} \quad (7.17)$$

since the encoder starts in the all-zero state  $s=0$ , and we use (7.15) to recursively compute  $\alpha_k(s)$ ,  $k = 0, 1, \dots, K-1$ , where  $K = h+m$  is the input sequence length,  $m$  is the memory length of the code.

- Similarly , the backward recursion begins at time  $k=K$  with the initial condition

$$\beta_K(s) = \begin{cases} 1 & s = 0 \\ 0 & s \neq 0 \end{cases} \quad (7.18)$$

since the decoder also ends in all-zero state, and we use (7.18) to recursively compute  $\beta_k(s)$ ,  $k =, K-1, \dots, 1, 0$

- We can write the **branch transition probability**

$$\begin{aligned} \gamma_k(s', s) &\equiv p(s, r_k \mid s',) = P(s' s, r_k,)/ P(s') \\ &= p(r_k \mid s', s) P(s \mid s') \\ &= p(r_k \mid s', s) P(u_k) \\ &= p(r_k \mid v_k) P(u_k) \end{aligned} \quad (7.19)$$

where  $u_k$  is the input bit necessary to cause the transition from state  $s'$  to state  $s$ ,  $P(u_k)$  is the *a priori probability* of this bit;  $v_k$  is the transmitted codeword associated with this transition  $s' \rightarrow s$ .

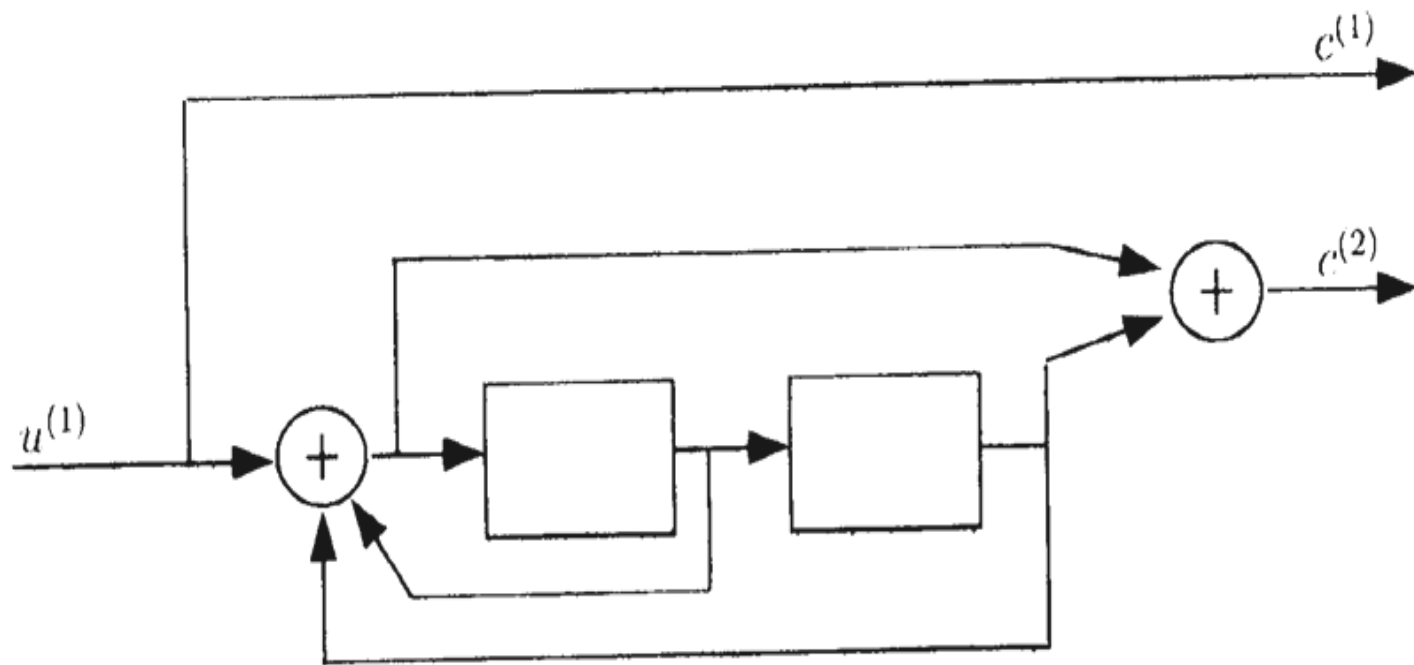
- Hence , the transition probability density  $\gamma_k (s', s)$  is given by the product of the *a priori* probability of the input bit  $u_k$  necessary for the transition and the conditional density of the received channel sequence for the value  $r_k$  given that the codeword  $v_k$  associated with the transition was transmitted.
- The *a priori* probability  $p(u_k)$  is derived in an iterative decoder from the output of the previous component decoder.

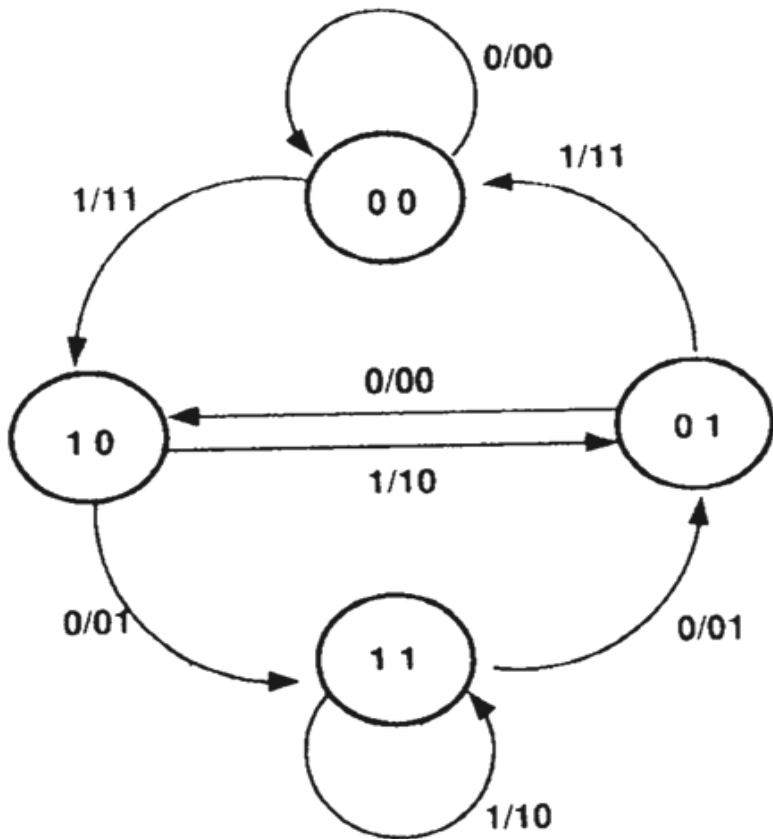
- **In the following , trellis representation of a convolutional code is used to illustrate the algorithm.**

**The functional block diagram of a (2,1,2) recursive convolutional code encoder is shown in ig.8.xx(a) .**

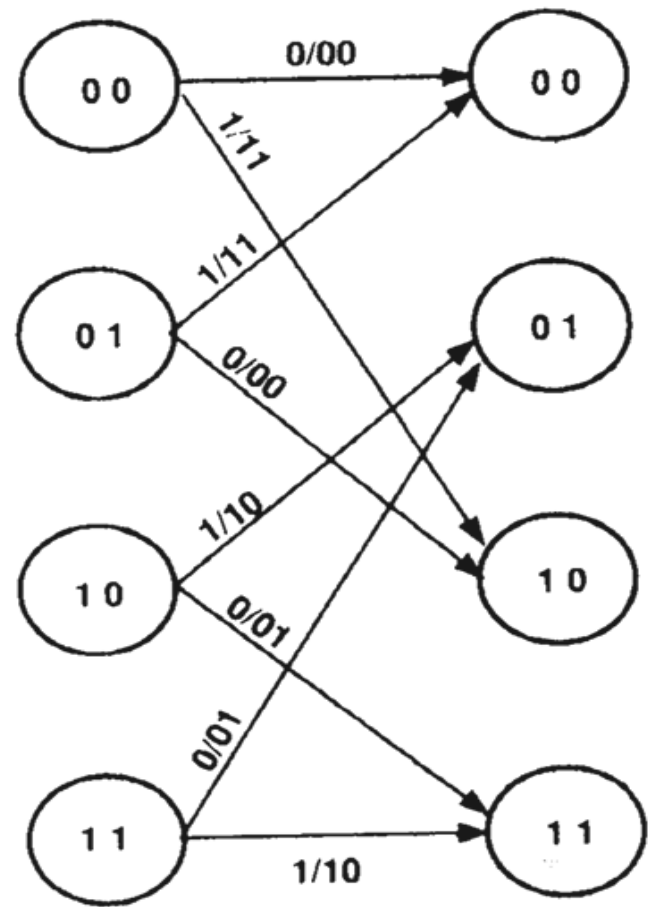
$$\mathbf{G} = [ 1 \quad (1+D^2)/1+D + D^2 \quad ]$$





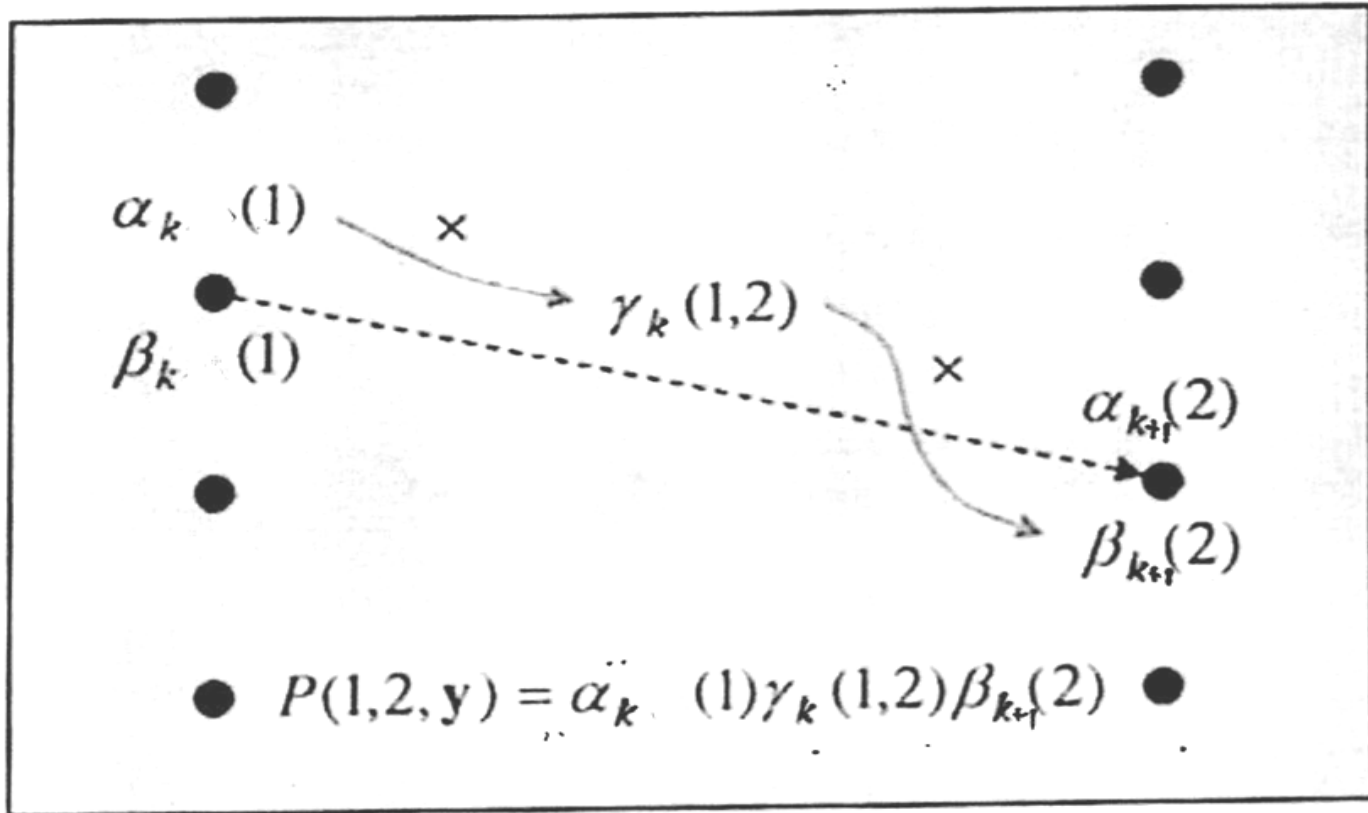


(a)



(b)

$P(s', s, y)$  can be expressed as the three-factor product  $\alpha_{k-1}(s') \gamma_k(s', s) \beta_k(s)$



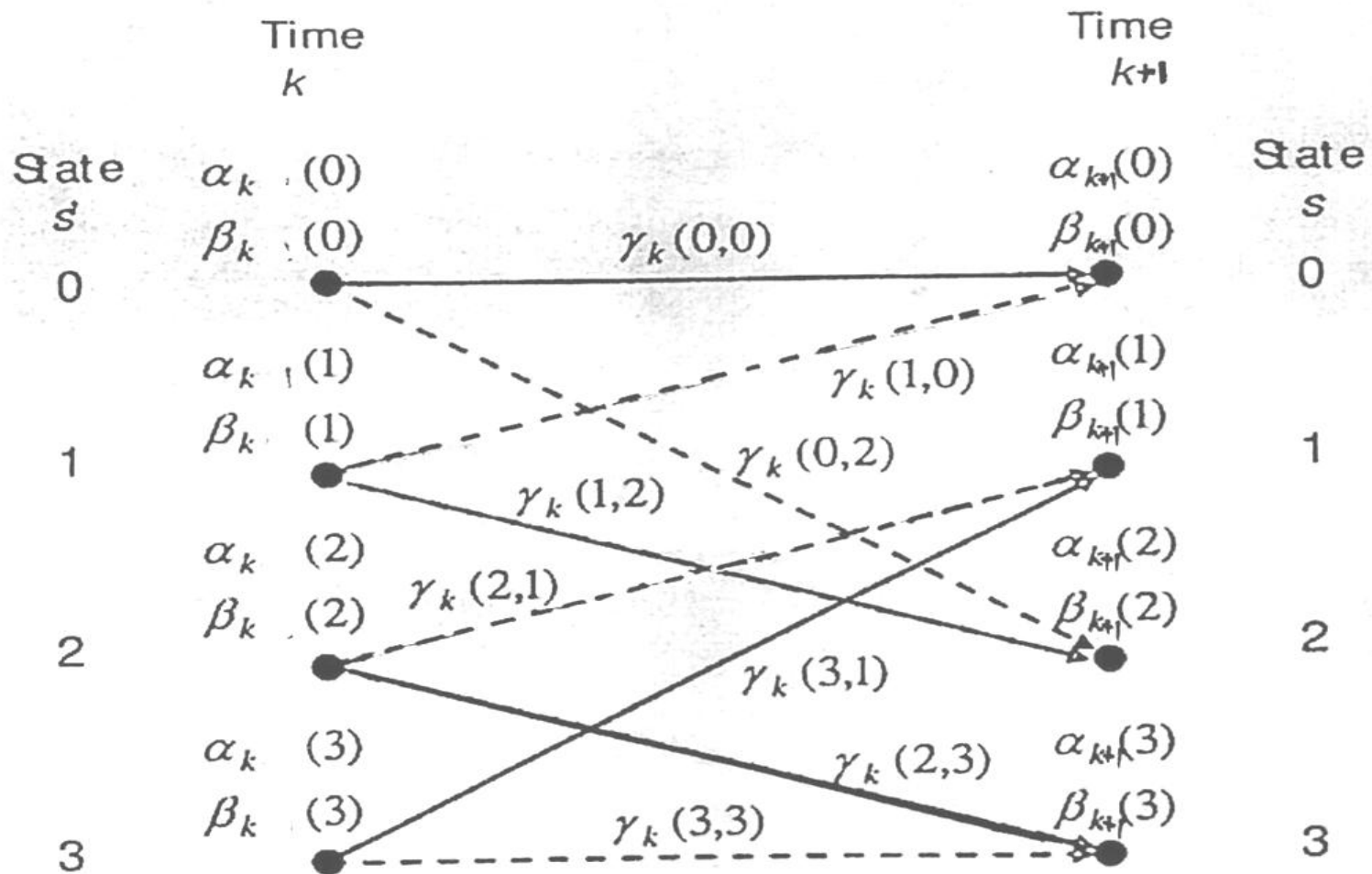
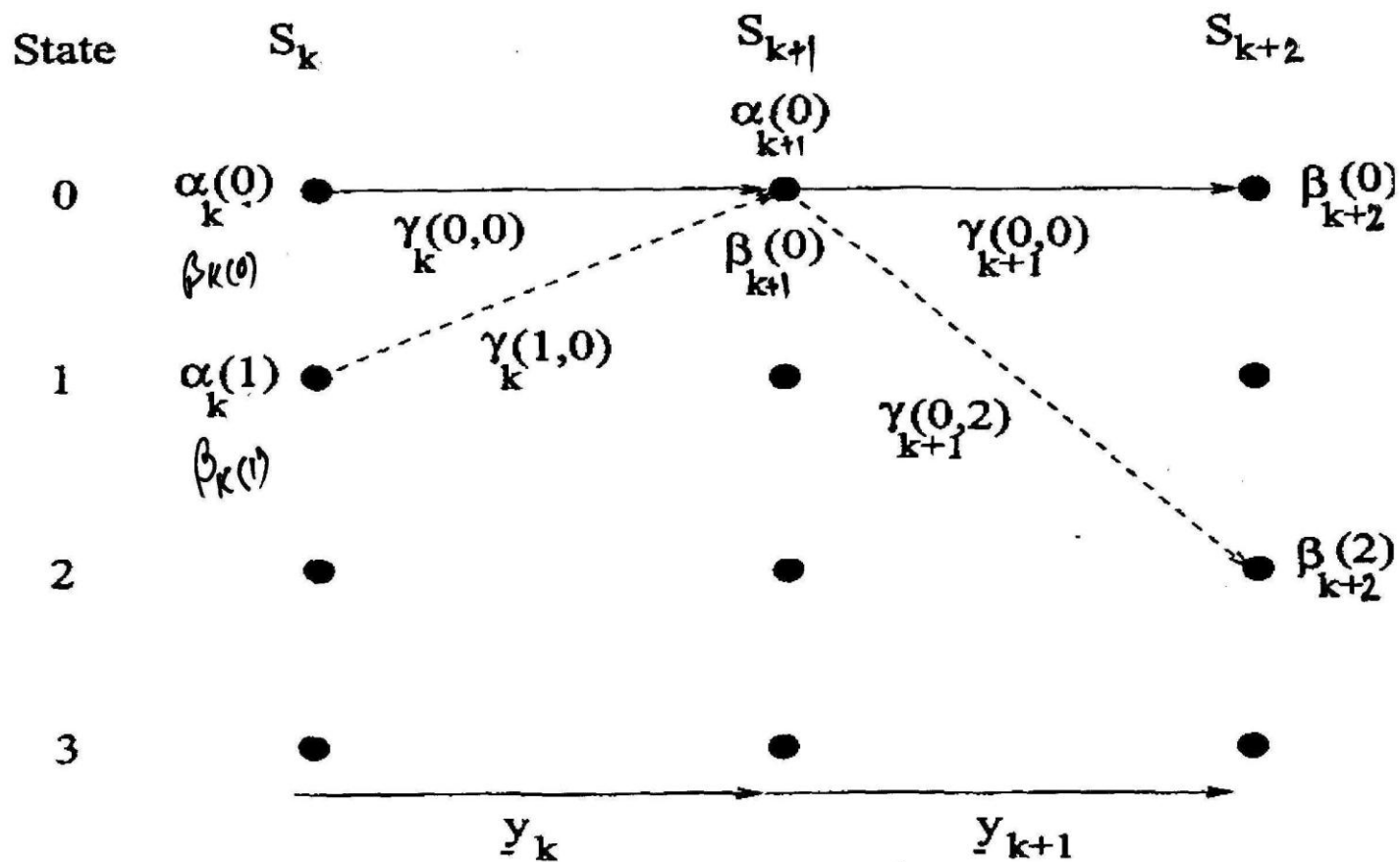


Fig. 3  $\alpha$ ,  $\beta$  and  $\gamma$  as trellis labels



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

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

**Fig. 4. Recursive calculation of  $\alpha_k(0)$  and  $\beta_k(0)$ .**

- From (7.8 ) and (7.10) , we can compute the conditional LLR of  $u_k$ , given the received value  $r_k$  .
  - The MAP algorithm finds  $\alpha_k(s)$  and  $\beta_{k+1}(s)$  for all states  $s$  throughout the trellis, i.e., for  $k = 0, 1, 2, \dots, K-1$  , and  $\gamma_k(s', s)$  for all possible transitions from state  $s_k = s'$  to state  $s_{k+1} = s$  , and again for  $k = 0, 1, 2, \dots, K-1$
- These values are then used to compute the conditional LLR  $L(u_k)$  that the MAP decoder delivers.

- **Summary of BCJR (MAP ) Algorithm :**

**The MAP decoding of a received sequence  $r$  to give the *a posteriori* LLR  $L(u_k)$  can be carried out as follows.**

- (1) Initialize forward and backward recursions ,  $\alpha_0(s)$ , and  $\beta_K(s')$  .**
- (2) As the channel values  $r_{ki}$  are received, they and the *a priori LLRs*  $L_a(u_k)$ , which are provided in an iterative turbo decoder by the other components , are used to calculate  $\gamma_k(s', s)$ , according to (7-12).**
- (3) As the channel values  $y_{kl}$  and the  $\gamma_k(s', s)$  values are calculated , the forward recursion from (7.15) can be used to calculate  $\alpha_k(s)$  based on  $\alpha_{k-1}(s)$  .**

- (4) Once all the channel values have been received , and  $\gamma_k (s', s)$  has been calculated for all  $k = 0, 1, 2, \dots, K-1$  , the backward recursion from (7.16) can be used to calculate the  $\beta_{k-1}(s')$  values based on the  $\beta_k (s')$  .**
- (5) Finally, all the calculated values of  $\alpha_k (s)$  ,  $\gamma_k (s', s)$  , and  $\beta_{k+1} (s')$  are used to calculate the values of  $L(u_k)$  .**

**Note : The complexity is about three times of Viterbi algorithm**



## 7.3 Logarithmic BCJR Algorithm :

### Log-MAP and Max-Log-MAP

- The log-MAP algorithm was proposed by **Robertson *et al*** in 1995 . It has performance close to that of the MAP algorithm, but at a fraction of its complexity.  
Also, it is easier to implement and numerically more stable .
- In the log-MAP algorithm, additions substitute the BCJR algorithm multiplications with the aid of the Jacobian logarithm ( The max operation).

$$\begin{aligned}\max^*(a,b) &= \ln ( e^a + e^b ) \\ &= \max (a,b) + \ln ( 1 + e^{-|a-b|} )\end{aligned}\quad (7.20)$$

The term  $\ln ( 1 + e^{-|a-b|} )$  is usually small which can be stored in a simple look-up table .

- The term  $\ln ( 1 + e^{-|a-b|} )$  is negligible in most practical applications. Thus ,  $\max^*(a,b)$  is replaced by  $\max (a,b)$  when  $| \max (a,b) | \geq 7$  .

■ **New variables are defined :**

$$A_k(s) = \ln \alpha_k(s)$$

$$B_k(s) = \ln \beta_k(s)$$

$$\Gamma_k(s', s) = \ln \gamma_k(s', s) \tag{7.21}$$

**With some mathematical manipulations, we can obtain the following equations :**

$$\Gamma_k(s', s) = \begin{cases} u_k L_a(u_k) / 2 + (L_c / 2) \sum_{i=1}^n v_{ki} r_{ki} & k = 0, 1, \dots, h-1 \\ \sum_{j=1}^n v_{kj} r_{kj} & k = h, h+1, \dots, K-1 \end{cases} \tag{7.22}$$

$$A_k(s) = \max_{s'}^* [A_{k-1}(s') + \Gamma_k(s', s)], \quad k = 0, 1, \dots, K-1 \tag{7.23}$$

$$B_k(s) = \max^*_S [B_{k+1}(s) + \Gamma_k(s', s)]$$

$$k = K-1, K-2, \dots, 1, 0 \quad (7.24)$$

The initial values of A and B in the terminal trellis are

$$A_0(s) = 0 \quad s=0$$

$$-\infty \quad s \neq 0$$

$$B_K(s) = 0 \quad s=0$$

$$-\infty \quad s \neq 0$$

$$(7.25)$$

Consequently, we have

$$L(u_k) = \max^*_{U_+} [A_k(s') + \Gamma_k(s', s) + B_{k+1}(s)]$$

$$- \max^*_{U_-} [A_k(s') + \Gamma_k(s', s) + B_{k+1}(s)]$$

$$(7.26)$$

## Summary :

### The log-BCJR Algorithm :

Step1. Initialize the forward and backward metrics  $A_0(s)$  and  $B_K(s)$  using (7.25) .

Step2. Compute the branch metrics  $\Gamma_k(s', s)$  using (7.22) .

Step3. Compute the forward metrics  $A_{k-1}(s)$  using (7.23) .

Step 4. Compute the backward metrics  $B_{k-1}(s)$ ,  
 $k = K, K-1, \dots, 1$ , using (7.24)

Step 5 . Compute the APP L-values  $L(u_k)$  using (7.26) .

Step 6. (optional) Compute the hard-decision  $u_k$

- The algorithm that compute  $L(u_k)$  using Eq. (7.26) is called the **log-MAP algorithm** ; if  $\max^*$  function is replaced by  $\max$  function , then the algorithm is called **Max-log- MAP algorithm**.

- The max-log-MAP algorithm relies on the MAP algorithm but significantly reduces the complexity by neglecting the correction term in (7.20) , that is,

$$\ln ( e^a + e^b ) \doteq \mathbf{max}^* (a,b )$$

### Remarks :

It was shown by Fossorier et al. in 1998 that the performance of a modified SOVA ( soft-output Viterbi algorithm ) is equivalent to the max-log-MAP algorithm if the soft-update rule is extended.

Fossorier, M.P. , Bunkert, F., Lin,S., and Hagenauer,J., “ On the Equivalence Between SOVA and Max-Log-MAP Decoding ,” IEEE Comm. Letters , vol. 2 , no.5 , pp. 137-139 , May 1998.

◆ **Note 1 :**

From  $\ln ( e^a + e^b ) = \max^* ( a, b ) = \max ( a, b ) + \ln ( 1 + e^{- | a-b | } )$

**we obtain the formula**

$$\begin{aligned} \ln \sum_{i=1}^n e^{a_i} &= \ln ( e^{a_1} + e^{a_2} + \dots + e^{a_n} ) \\ &= \ln ( \Delta + e^{a_n} ) \end{aligned}$$

with  $\Delta = e^{a_1} + e^{a_2} + \dots + e^{a_{(n-1)}} = e^\delta$

Therefore ,

$$\begin{aligned} \ln \sum e^{a_i} &= \ln ( e^\delta + e^{a_n} ) \\ &= \max ( \delta + a_n ) + \ln ( 1 + e^{- | \delta - a_n | } ) \\ &= \dots \\ &= A_M + \ln [ 1 + \sum e^{(A_i - A_M)} ] \end{aligned}$$

**where**  $A_M = \max ( a_i ) \quad i \neq m$

◆ **Note 2:**

$$\max^* ( x, y, z ) = \max^* ( \max^* ( x, y ), z )$$

## 7.4 BCJR for Decoding BPSK Signal over AWGN Channel

- For a system with memoryless AWGN channel and BPSK modulation, The conditional received sequence probability density  $p(\mathbf{r}_k | \mathbf{v}_k)$  is given by

$$\begin{aligned} p(\mathbf{r}_k | \mathbf{v}_k) &= \prod_{i=1}^n p(r_{ki} | v_{ki}) \\ &= \prod_{i=1}^n \sqrt{(E_c / \pi N_0)} \exp\{- (E_c / N_0) (r_{ki} - a v_{ki})^2\} \end{aligned} \quad (7.27)$$

where

$r_{ki}$  and  $v_{ki}$  are the individual bits within the received and transmitted codeword, respectively,

$n$  is the number of these bits in the codeword, and  $a$  is the channel gain .

$a = 1$  for non-fading AWGN channel.

$E_c$  is the transmitted energy per coded bit ,  $N_0/2$  is the power spectral density of the noise .

$E_c = R_c E_b$  , and  $E_b$  is the energy of a message bit .

- $(r_k - v_k)^2 = \sum_i (r_{ki} - a v_{ki})^2$  is the squared Euclidean distance between the received branch and transmitted branch at time  $k$  .



- For a **continuous –output AWGN channel**, if  $s' \rightarrow s$  is a valid state transition ,

$$\begin{aligned} \gamma_k(s', s) &= p(\mathbf{r}_k \mid \mathbf{v}_k) p(u_k) \\ &= P(u_k) \left[ \sqrt{(E_c / \pi N_0)} \right]^n \\ &\quad \exp \left[ - (E_s / N_0) \left\| (\mathbf{r}_k - \mathbf{v}_k) \right\|^2 \right] \end{aligned}$$

The constant factor  $\left[ \sqrt{(E_c / \pi N_0)} \right]^n$  is usually dropped for simplicity.

Thus, we have a **modified branch metric**

$$\gamma_k(s', s) = p(u_k) \exp \left( - E_c / N_0 \left\| (\mathbf{r}_k - \mathbf{v}_k) \right\|^2 \right) \quad (7.28)$$

- $L_a(u_k) = \ln \left[ p(u_k = +1) / p(u_k = -1) \right] \quad (7.29)$   
is the *a priori* L-value of the bit  $u_k$ .

- We can express the a priori probabilities  $P(u_k = \pm 1)$  as exponential terms by written

$$\begin{aligned}
 p(u_k = \pm 1) &= [ p(u_k = + 1) / p(u_k = - 1) ]^{\pm 1} / \\
 &\quad \{ 1 + [ P(u_k = + 1) / P(u_k = - 1) ]^{\pm 1} \} \\
 &= \exp [ L_a (u_k) ]^{\pm 1} / \{ 1 + \exp [ L_a (u_k) ]^{\pm 1} \} \\
 &= \exp [- L_a (u_k) / 2 ] \exp [ u_k L_a (u_k) / 2 ] / \\
 &\quad \{ 1 + \exp [- L_a (u_k) ] \} \\
 &= C_{1k} \exp [ u_k L_a (u_k) / 2 ] \tag{7.30} \\
 &\quad k = 0, 1, \dots, h-1
 \end{aligned}$$

where, since L-values do not depend on the value of their argument , the parameter  $A_k$  is independent of the actual value of  $u_k$  .

$$C_{1k} = \exp [- L_a (u_k) / 2 ] / \{ 1 + \exp [- L_a (u_k) ] \}$$

- For termination bits  $u_k$ ,  $k = h, \dots, h+m-1 = K-1$ , where  $p(u_k) = 1$  and,  $L_a(u_k) = \pm \infty$  for each valid state transition we simply use (7.28).

Thus we can write the modified branch metric as

$$\begin{aligned}
 \gamma_k(s', s) &= C_{1k} \exp [u_k L_a(u_k)/2] \\
 &\quad \exp [ - (E_c/N_0) \| (r_k - v_k) \|^2 ] = \dots \\
 &= C_{1k} C_{2k} \exp [u_k L_a(u_k)/2] \\
 &\quad \exp [ (L_c / 2) (r_k \cdot v_k) ] \\
 &\hspace{15em} k=0,1,\dots, h-1 \hspace{10em} (7.31)
 \end{aligned}$$

$$\begin{aligned}
 \gamma_k(s', s) &= p(u_k) \exp [ - (E_c/N_0) \| (y_k - x_k) \|^2 ] = \dots \\
 &= C_{2k} \exp [ (L_c / 2) (r_k \cdot v_k) ] \\
 &\hspace{15em} k = h, \dots, K-1 \hspace{10em} (7.32)
 \end{aligned}$$

where  $C_{2k} = \| r_k \|^2 + n$  is a constant independent of the codeword  $v_k$ , and  $L_c = 4 E_s/N_0$  is the **channel reliability factor**.

- Thus in the calculation of  $p(s', s, y)$ , the factors  $\prod_{k=0}^{h-1} C_{1k}$  and  $\prod_{k=0}^{K-1} C_{2k}$  are both contained in the numerators and denominators summations, we can drop these factors and use the exponential function

$$\gamma_k(s', s) = \exp [ u_k L_a(u_k)/2 ] \exp [ (L_c / 2 ) (\mathbf{r}_k \cdot \mathbf{v}_k ) ]$$

$$k = 0, 1, \dots, h-1$$

(7.33a)

$$\gamma_k(s', s) = \exp [ (L_c / 2 ) (\mathbf{r}_k \cdot \mathbf{v}_k ) ]$$

$$k = h, h+1, \dots, K-1$$

(7.33b)

as a simplified branch metric .

- Note that **when the input bits are equally likely,  $L^a(u_k) = 0$** , and the simplified branch metric is given by

$$\gamma_k(s', s) = \exp [ (L_c / 2 ) (\mathbf{r}_k \cdot \mathbf{v}_k ) ]$$

$$k = 0, 1, \dots, h, h+1, \dots, K-1$$

(7.34)

## Example ( Lin & Costello, p. 572)

### BCJR Decoding of a (2,1,1) systematic recursive convolutional code on an AWGN Channel.

- The generator matrix of the (2,1,1) systematic recursive convolutional code is given by

$$G(D) = [ 1 \quad 1/(1+D) ]$$

The block diagram of the encoder and the corresponding trellis diagram are shown in the following figure .

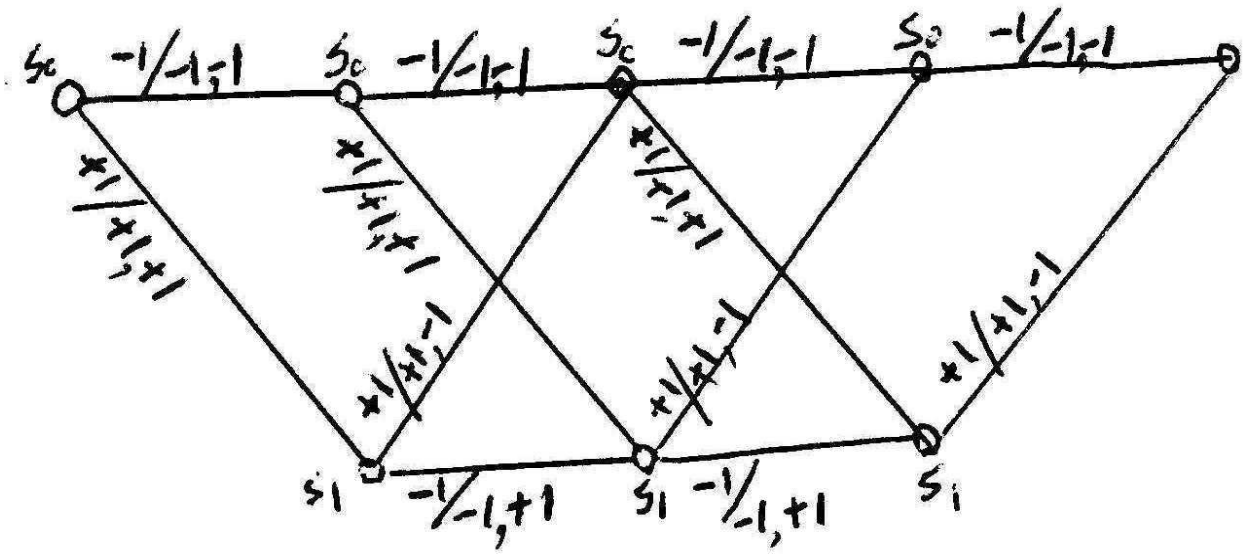
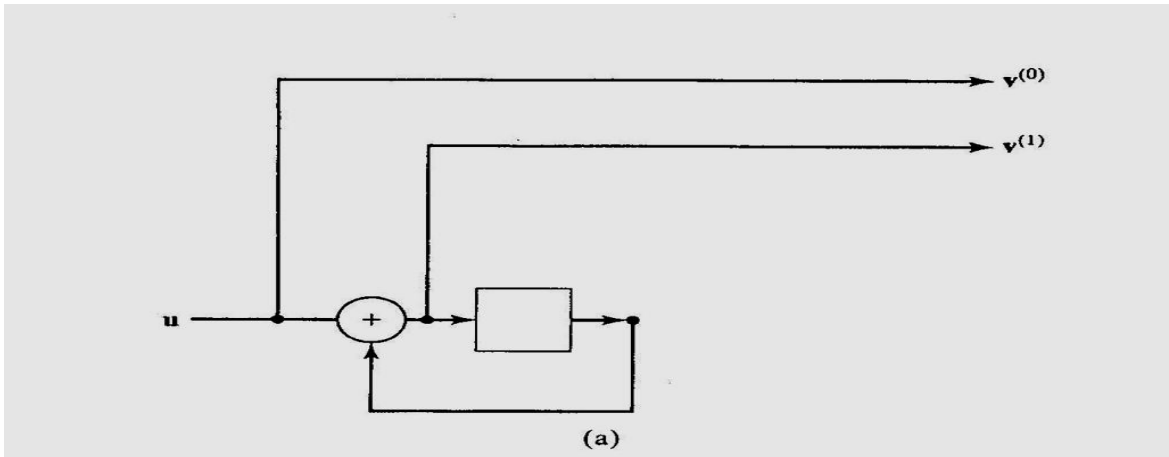
- The input sequence has a length of 4 and mapping rule is

$$0 \rightarrow -1, \quad 1 \rightarrow +1$$

- Assume that the channel has SNR of  $E_s/N_0 = 1/4$  (-6.02 dB) and a (normalized by  $\sqrt{E_s}$ ) receiver vector

$$\begin{aligned} R &= ( r_0 \quad r_1 \quad r_2 \quad r_3 ) = ( r_1^{(1)} \quad r_1^{(2)} \quad r_1^{(1)} \quad r_1^{(2)} \quad r_2^{(1)} \quad r_2^{(2)} \quad r_3^{(1)} \quad r_3^{(2)} ) \\ &= ( 0.8 \quad 0.1 \quad 1.0 \quad -0.5 \quad -1.8 \quad 1.1 \quad 1.6 \quad -1.6 ) \end{aligned}$$

Note :  $E_b/N_0 = E_s/(3/8)N_0 = 2/3$



- Assuming that the a priori probability of the information bits are equally likely , i.e.  $L_a(u_k) = 0$  ,  $k = 1,2 ,..$  , the log-domain branch metrics are calculated as follows.

$$\begin{aligned} \Gamma_0 ( s_0 , s_0 ) &= ( -1/2 ) L_a(u_0) + (1/2) ( \mathbf{r}_0 \cdot \mathbf{v}_0 ) \\ &= (1/2) ( - 0.8-0.1 ) = - 0.45 \end{aligned}$$

$$\begin{aligned} \Gamma_0 ( s_0 , s_1 ) &= (1/2) L_a(u_0) + (1/2) ( \mathbf{r}_0 \cdot \mathbf{v}_0 ) \\ &= (1/2) ( 0.8 +0.1 ) = 0.45 \end{aligned}$$

$$\begin{aligned} \Gamma_1 ( s_0 , s_0 ) &= ( -1/2 ) L_a(u_1) + (1/2) ( \mathbf{r}_1 \cdot \mathbf{v}_1 ) \\ &= (1/2) ( -1.0 + 0.5 ) = - 0.25 \end{aligned}$$

$$\begin{aligned} \Gamma_1 ( s_0 , s_1 ) &= (1/2) L_a(u_1) + (1/2) ( \mathbf{r}_1 \cdot \mathbf{V}_1 ) \\ &= (1/2) ( 1.0-0.5 ) = 0.25 \end{aligned}$$

$$\begin{aligned} \Gamma_1 ( s_1 , s_0 ) &= (1/2) L_a(u_1) + (1/2) ( \mathbf{r}_1 \cdot \mathbf{v}_1 ) \\ &= (1/2) ( -1.0 + 0.5 ) = 0.75 \end{aligned}$$

$$\begin{aligned} \Gamma_1 ( s_1 , s_1 ) &= ( -/2 ) L_a(u_1) + (1/2) ( \mathbf{r}_1 \cdot \mathbf{v}_1 ) \\ &= (1/2) ( -1.0 - 0.5 ) = - 0.75 \end{aligned}$$

$$\begin{aligned} \Gamma_2 ( s_0 , s_0 ) &= (-1/2) L_a(u_2) + (1/2) ( \mathbf{r}_2 \cdot \mathbf{v}_2 ) \\ &= (1/2) ( 1.8 - 1.1 ) = \mathbf{0.35} \end{aligned}$$

$$\begin{aligned} \Gamma_2 ( s_0 , s_1 ) &= (1/2) L_a(u_2) + (1/2) ( \mathbf{r}_2 \cdot \mathbf{v}_2 ) \\ &= (1/2) ( -1.8 + 1.1 ) = \mathbf{-0.35} \end{aligned}$$

$$\begin{aligned} \Gamma_2 ( s_1 , s_0 ) &= (1/2) L_a(u_2) + (1/2) ( \mathbf{r}_2 \cdot \mathbf{v}_2 ) \\ &= (1/2) ( -1.8 - 1.1 ) = \mathbf{-1.45} \end{aligned}$$

$$\begin{aligned} \Gamma_2 ( s_1 , s_1 ) &= ( -1/2 ) L_a(u_2) + (1/2) ( \mathbf{r}_2 \cdot \mathbf{v}_2 ) \\ &= (1/2) ( 1.8 + 1.1 ) = \mathbf{1.45} \end{aligned}$$

$$\begin{aligned} \Gamma_3 ( s_0 , s_0 ) &= (1/2) ( \mathbf{r}_3 \cdot \mathbf{v}_3 ) \\ &= (1/2) ( -1.6 + 1.6 ) = \mathbf{0} \end{aligned}$$

$$\begin{aligned} \Gamma_3 ( s_1 , s_0 ) &= (1/2) ( \mathbf{r}_3 \cdot \mathbf{v}_3 ) \\ &= (1/2) ( 1.6 + 1.6 ) = \mathbf{1.60} \end{aligned}$$



■ Then we calculate log-domain metrics *using* (7.23 ) as follows.

$$A_1(s_0) = \Gamma_0 ( s_0 , s_0 ) + A_0( s_0 ) = -0.45 + 0 = -0.45$$

$$A_1(s_1) = \Gamma_0 ( s_0 , s_1 ) + A_0( s_0 ) = 0.45 + 0 = 0.45$$

$$\begin{aligned} A_2(s_0) &= \max^* \{ [\Gamma_1 ( s_0 , s_0 ) + A_1( s_0 )] , [\Gamma_1 ( s_1 , s_0 ) + A_1( s_1 )] \} \\ &= \max^* \{ [- 0.25 + ( -0.45 )] , [ ( 0.75 ) + ( =0.45 ) ] \} \\ &= \max^*( -0.70 , +1.20 ) \\ &= 1.20 + \ln ( 1 + e^{-1.9} ) = 1.34 \end{aligned}$$

$$\begin{aligned} A_2(s_1) &= \max^* \{ [\Gamma_1 ( s_0 , s_1 ) + A_1( s_0 )] , [\Gamma_1 ( s_1 , s_1 ) + A_1( s_1 )] \} \\ &= \max^* ( -0.20 , - 0.30 ) = 0.44 \end{aligned}$$

■ Similarly , we calculate log-doman backward metrics as follows.

$$B_3(s_0) = \Gamma_3 ( s_0 , s_0 ) + B_4( s_0 ) = 0 + 0 = 0$$

$$B_3(s_1) = \Gamma_3 ( s_1 , s_0 ) + B_4( s_0 ) = 1.60 + 0 = 1.60$$

$$\begin{aligned} B_2(s_0) &= \max^* \{ [\Gamma_2 ( s_0 , s_0 ) + B_3( s_0 ) ] , [\Gamma_2 ( s_0 , s_1 ) + B_3( s_1 ) ] \} \\ &= \max^* \{ [ 0.35 + 0 ] , [ -0.35 + 1.60 ] \} \\ &= \max^* ( 0.35 , 1.25 ) = 1.25 + \ln ( 1 + e^{-0.90} ) = 1.59 \end{aligned}$$

$$\begin{aligned} B_2(s_1) &= \max^* \{ [\Gamma_2 ( s_1 , s_0 ) + B_3( s_0 ) ] , [\Gamma_2 ( s_1 , s_1 ) + B_3( s_1 ) ] \} \\ &= \max^*( -1.45 , 3.05 ) = 3.06 \end{aligned}$$

$$\begin{aligned}
 B_1(s_0) &= \max^* \{ [ \Gamma_1 ( s_0 , s_0 ) + B_2( s_0 ) ] , [ \Gamma_1( s_0 , s_1 ) + B_2( s_1 ) ] \} \\
 &= \max^*(1.34 , 3.31 ) = 3.44
 \end{aligned}$$

$$\begin{aligned}
 B_1(s_1) &= \max^* \{ [ \Gamma_1 ( s_1 , s_0 ) + B_2( s_0 ) ] , [ \Gamma_1( s_0 , s_1 ) + B_2( s_1 ) ] \} \\
 &= \max^*( 2.34 , 2.31 ) = 3.02
 \end{aligned}$$

- Finally , we calculate the APP L-values for the three information bits as follows.

$$\begin{aligned}
 L(\mathbf{u}_0) &= [ B_1(s_1) + \Gamma_0 ( s_0 , s_1 ) + A_0 ( s_0 ) ] \\
 &\quad - [ B_1(s_0) + \Gamma_0 ( s_0 , s_0 ) + A_0 ( s_0 ) ] \\
 &= 3.47 - 2.99 = 0.48
 \end{aligned}$$

$$\begin{aligned}
 L(\mathbf{u}_1) &= \max^* \{ [ B_2(s_0) + \Gamma_1 ( s_1 , s_0 ) + A_1 ( s_1 ) ] , [ B_2(s_1) + \\
 &\quad \Gamma_1 ( s_0 , s_1 ) + A_1 ( s_0 ) ] \\
 &\quad - [ B_2(s_0) + \Gamma_1 ( s_0 , s_0 ) + A_1( s_0 ) ] + [ B_2(s_1) + \\
 &\quad \Gamma_1 ( s_1 , s_1 ) + A_1 ( s_1 ) ] \} \\
 &= \max^* ( 2.79 , 2.86 ) - \max^* ( 0.89 , 2.76 ) = 0.62
 \end{aligned}$$

$$\begin{aligned}
\mathbf{L}(\mathbf{u}_2) &= \max^* \{ [B_3(s_0) + \Gamma_2(s_1, s_0) + A_2(s_1)], [B_3(s_1) + \\
&\quad \Gamma_2(s_0, s_1) + A_2(s_0)] \\
&\quad - [B_3(s_0) + \Gamma_2(s_0, s_0) + A_2(s_0)] + [B_3(s_1) + \\
&\quad \Gamma_2(s_1, s_1) + A_2(s_1)] \} \\
&= \max^* (-1.01, 2.59) - \max^* (1.69, 3.49) = -1.02
\end{aligned}$$

- The hard-decision outputs of the BCJR decoder for the three information bits are

$$\mathbf{u}^\wedge = (1, 1, -1)$$

## 7.5 Application of BCJR Algorithm : Iterative Decoding of Turbo Codes

- Consider a rate  $1/3$  systematic convolutional encoder in which **the first coded bit,  $v_{k0}$ , is equal to the information bit  $u_k$ .**

In this case, the *a posteriori* log-likelihood ratio  $L(u_k)$  can be generally decomposed into a sum of three elements :

$$L(u_k) = L_c r_k + L_a(u_k) + L_e(u_k) \quad (7.35)$$

The first two terms are related with the information bit  $u_k$ . The third term,  $L_e(u_k)$  is the extrinsic information provided by the decoder based on both the received sequence and on the *a priori* information, excluding both the received sample representing the systematic bit  $u_k$  and the *a priori* information  $L_a(u_k)$ . Derivation is given in Appendix 7A

- The basic structure of a turbo decoder is shown in Fig. 8.xx . Here, we assume a rate 1/3 parallel concatenated code without puncturing. It uses two MAP decoders.
- At each time unit  $k$  , three output values are received from the channel , one for the information bit  $u_k$  , denoted by  $r_k^{(0)}$  , and two for the parity bits , denoted by  $r_k^{(1)}$  and  $r_k^{(2)}$  .

The received sequence can be expressed by a  $3K$ -dimensional vector  $\mathbf{r}$  as

$$\begin{aligned} \mathbf{r} &= (r_0^{(0)} r_0^{(1)} r_0^{(2)} , r_1^{(0)} r_1^{(1)} r_1^{(2)} , \dots , r_{K-1}^{(0)} r_{K-1}^{(1)} r_{K-1}^{(2)} ) \\ &= (\mathbf{r}^{(0)} \quad \mathbf{r}^{(1)} \quad \mathbf{r}^{(2)} ) \end{aligned} \quad (7.36)$$

Also, let each transmitted bit be represented using the mapping “0”  $\rightarrow$  -1 and “1”  $\rightarrow$  +1 .

- For an AWGN channel with soft ( unquantized) outputs , the LLR of a transmitted information bit  $u_k$  , denoted as the  $L(u_k | r_k^{(0)})$  , is expressed by

$$\begin{aligned}
 L(u_k | r_k^{(0)}) &= \ln \{ p(u_k = +1 | r_k^{(0)}) / p(u_k = -1 | r_k^{(0)}) \} \\
 &= \ln \{ p(r_k^{(0)} | u_k = +1) p(u_k = +1) / \\
 &\quad p(r_k^{(0)} | u_k = -1) p(u_k = -1) \} \\
 &= \ln \{ \exp [ - ( E_s / N_0 ) ( r_k^{(0)} - 1 )^2 ] / \\
 &\quad \exp [ - ( E_s / N_0 ) ( r_k^{(0)} + 1 )^2 ] \} \\
 &\quad + \ln \{ p(u_k = +1) / p(u_k = -1) \} \\
 &= (4 E_s / N_0) r_k^{(0)} + L_a(u_k) \\
 &= L_c r_k^{(0)} + L_a(u_k) \tag{7.37}
 \end{aligned}$$

where  $L_c = 4 E_s / N_0$  is the channel reliability factor and  $L_a(u_k)$  is the a priori L-value of the bit  $u_k$  .

- In the case of a **transmitted parity bit**  $v_k^{(j)}$  , giving the received value  $r_k^{(j)}$  ,  $j = 1, 2$  , the L-value ( before decoding ) is given by

$$\begin{aligned} L(v_k^{(j)} \mid r_k^{(j)}) &= L_c r_k^{(j)} + L_a(v_k^{(j)}) \\ &= L_c r_k^{(j)} , \quad j = 1, 2 \end{aligned} \quad (7.38)$$

since in a linear code with equally likely information bits , the parity bits are also equally to be +1 or -1 , and thus the a priori L-values of the parity bits are 0 ;that is ,

$$L_a(v_k^{(j)}) = 0 , \quad j = 1, 2 \quad (7.39)$$

Note that  $L_a(u_k)$  also equals 0 for the first iteration of the decoder 1 but that thereafter the *a priori* L-values of the information bits are replaced by extrinsic l-values from the other decoder ( say , decoder 2 ).

- **Iterative decoding Process**

a. The received soft channel L-values  $L_c r_k^{(0)}$  and  $L_c r_k^{(1)}$  enter decoder 1 , and  $L_c r_k^{(0)}$  and the properly interleaved soft channel L-values  $L_c r_k^{(2)}$  enter decoder 2 .

The output of decoder 1 contains two parts :

$$(1) L^{(1)}(u_k) = \ln \left\{ \frac{p(u_k = +1 \mid \mathbf{r}^{(0)}, \mathbf{r}^{(1)}; L_a^{(1)})}{p(u_k = -1 \mid \mathbf{r}^{(0)}, \mathbf{r}^{(1)}; L_a^{(1)})} \right\} \quad (7.40)$$

$$(2) L_e^{(1)}(u_k) = L^{(1)}(u_k) - [L_c r_k^{(0)} + L_e^{(1)}(u_k)] \quad (7.41)$$

where  $L_a^{(1)} = [L_a^{(1)}(u_0), L_a^{(1)}(u_1), \dots, L_a^{(1)}(u_{K-1})]$  is *a priori* input vector for decoder 1

The extrinsic information  $L_e^{(1)}(u_k)$ , after interleaving, is then passed to the input of decoder 2 as *a priori* value  $L_2^{(2)}(u_k)$ .

It is noted that we assume  $L_a^{(1)}(u_k) = 0$  in the first iteration .



**b. The output of decoder 2 contains two parts :**

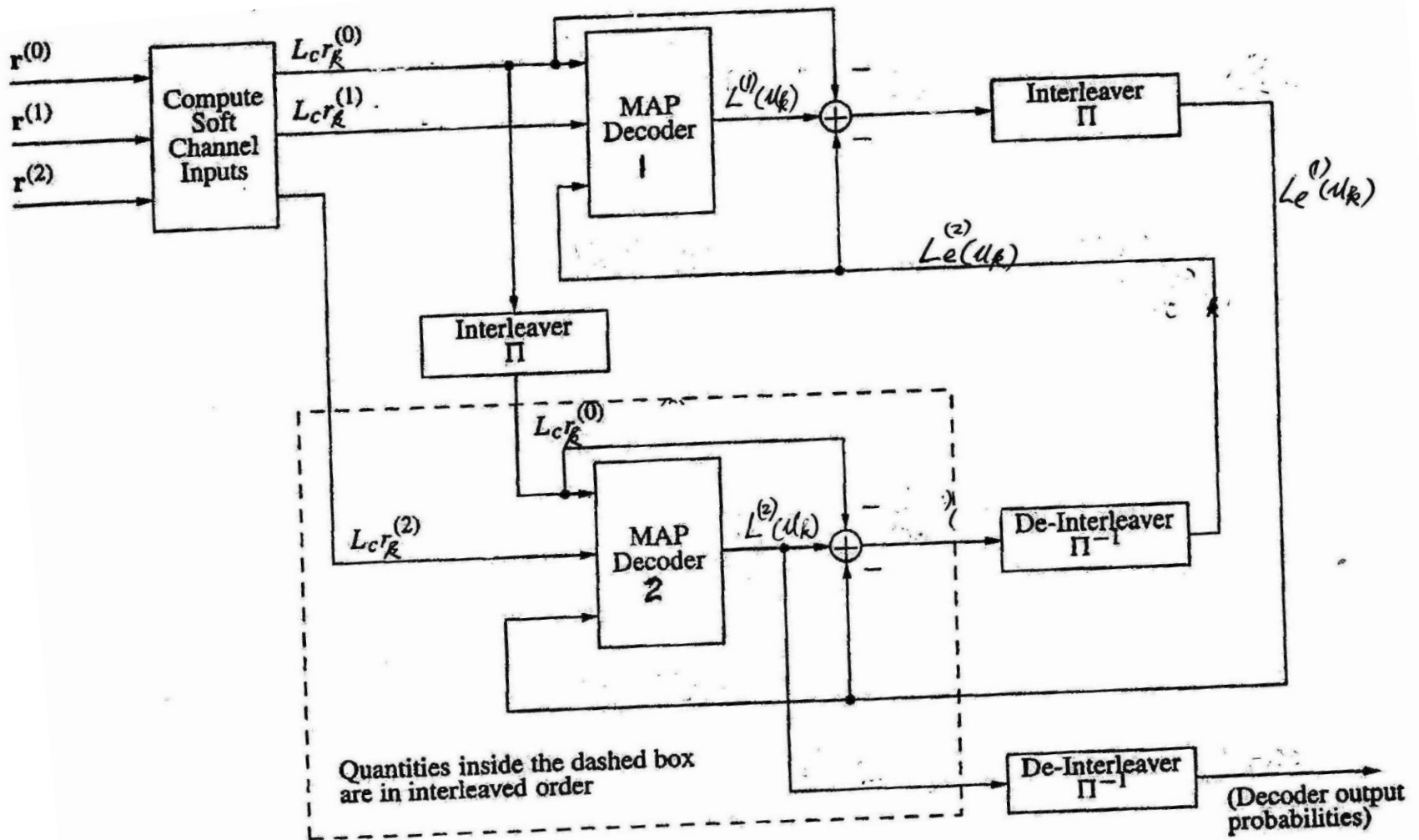
$$(1) L^{(2)}(u_k) = \ln \left\{ \frac{p(u_k = +1 \mid \mathbf{r}^{(0)}, \mathbf{r}^{(2)}; \mathbf{L}_a^{(2)})}{p(u_k = -1 \mid \mathbf{r}^{(0)}, \mathbf{r}^{(2)}; \mathbf{L}_a^{(2)})} \right\} \quad (7.42)$$

$$(2) L_e^{(2)}(u_k) = L^{(2)}(u_k) - [L_c r_k^{(0)} + L_e^{(1)}(u_k)] \quad (7.43)$$

The extrinsic information  $L_e^{(2)}(u_k)$ , after interleaving, is then passed to the input of decoder 2 as *a priori* value  $L_a^{(1)}(u_k)$ .

**c. Decoding then proceeds iteratively. With each decoder passing its respectively extrinsic L-values back to the other decoder. This results in a turbo effect in which each estimate becomes successively more reliable. After a sufficient number of iterations, the decoded information bits are determined from the *a posteriori* L-values  $L^{(2)}(u_k)$ ,  $k = 0, 1, 2, \dots, K-1$ .**

Fig. 8. Block diagram of a turbo decoder



# Appendix 7A :

## BPSK signal transmitted over AWGN channel

- The probability  $p(\mathbf{r}_k | \mathbf{v}_k)$  that  $n$  values  $\mathbf{r}_k = r_{k1} r_{k2} \dots r_{kn}$  are received given  $L$  values  $\mathbf{v}_k = v_{k1} v_{k2} \dots v_{kn}$  were transmitted will be equal to the product of the individual probabilities  $p(r_{ki} | v_{ki}), i = 1, 2, \dots, n$ .

In a memoryless channel, the successive transmissions are statistically independent.

$$p(\mathbf{r}_k | \mathbf{v}_k) = \prod_{i=1}^n p(r_{ki} | v_{ki}) \quad (\text{A-1})$$

- With BPSK modulation, the transmitted signals have amplitudes  $v_{ki} E_c$ , where  $v_{ki} = +1$  or  $-1$ , and  $E_c$  is the energy transmitted per code bit.
- Let us consider an AWGN channel with noise power spectral density  $N_0/2$  and fading amplitude  $a$ .

- At the receiver's matched filter output, the signal amplitude is now  $r'_{ki} = \pm a (\sqrt{E_c}) + w'$ , where  $w'$  is a sample of Gaussian noise with zero mean and variance

$$\sigma_{w'}^2 = N_0/2 .$$

Normalizing amplitudes in the receiver we get

$$r_{ki} = r'_{ki} / (\sqrt{E_c}) = a v_{ki} + w$$

where the noise  $w$  has variance  $\sigma_w^2 = N_0 / (2 E_c)$

Finally we have

$$p(r_{ki} | v_{ki}) = \sqrt{(E_c / \pi N_0)} \exp\{- (E_c / N_0) (r_{ki} - a v_{ki})^2\} \quad (\text{A-2})$$

and then

$$\begin{aligned} p(r_k | v_k) &= [\sqrt{(E_c / \pi N_0)}]^n \exp\{- (E_c / N_0) [\sum_{i=1}^n r_{ki}^2 + a^2 \sum_{i=1}^n v_{ki}^2]\} \exp\{2a (E_c / N_0) \sum_{i=1}^n r_{ki} v_{ki}\} \\ &= C_{2i} \exp\{2a (E_c / N_0) \sum_{i=1}^n r_{ki} v_{ki}\} \quad (\text{A-3}) \end{aligned}$$

The product factors  $C_{2i}$  do not depend either on the  $u_k$  sign or the codeword  $v_k$ .

## Appendix 7B :

Derivation of  $L(u_k) = L^a(u_k) + L_c y_{k1} + L^e(u_k)$  (7.35)

- For a  $1/n$  systematic convolutional code , the first coded bit  $x_{k1}$  is equal to the first coded bit  $y_{k1}$  .

From the relation

$$\gamma_k(s', s) = \exp [u_k L^a(u_k)/2 ] \exp [ (L_c / 2 ) (y_k \cdot x_k ) ] \\ k=1,2,\dots, K \quad (\text{A-4})$$

where  $L_c = 4a R_c E_b / N_0$  . Then , we have

$$\gamma_k(s', s) = \exp [u_k L^a(u_k)/2 ] \exp [ (L_c / 2 ) \sum_{j=2}^n (y_{kj} x_{kj} ) ] \\ (\text{A-5})$$

Let us define

$$\chi_k(s', s) = \exp [ (L_c / 2 ) \sum_{j=2}^n (y_{kj} x_{kj} ) ] \quad (\text{A-6})$$

- If  $n = 2$  (e.g., the (2,1,2) RSC as the constituent code for turbo code), then  $\chi_k(s', s) = \exp [ (L_c(y_{k2} \mathbf{x}_{k2}) / 2) ]$   
(A-7)

Then we get

$$\gamma_k(s', s) = \exp\{ [u_k L^a(u_k) + L_c(y_{k2} \mathbf{x}_{k2})] / 2 \} \chi_k(s', s)$$

(A-8)

The APP L-value from (A-2)

$$\begin{aligned} L(u_k) &= \ln \{ \sum_{U+} p(s_{k-1}=s', s_k=s, y) / \sum_{U..} (s_{k-1}=s', s_k=s, y) \} \\ &= \ln \{ \sum_{U+} \beta_k(s) \chi_k(s', s) \alpha_{k-1}(s') \exp [ u_k L^a(u_k) \\ &\quad + L_c(y_{k1}) ] / 2 \} / \\ &\quad \sum_{U..} \beta_k(s) \chi_k(s', s) \alpha_{k-1}(s') \exp [ u_k L^a(u_k) \\ &\quad + L_c(y_{k1}) ] / 2 \} \end{aligned}$$

(A-9)

**Then**

$$L(u_k) = L^a(u_k) + L_c y_{k1} + \sum_{U+} \beta_k(s) \chi_k(s', s) \alpha_{k-1}(s') / \sum_{U--} \beta_k(s) \chi_k(s', s) \alpha_{k-1}(s') \quad (\text{A-10})$$

**We now define**

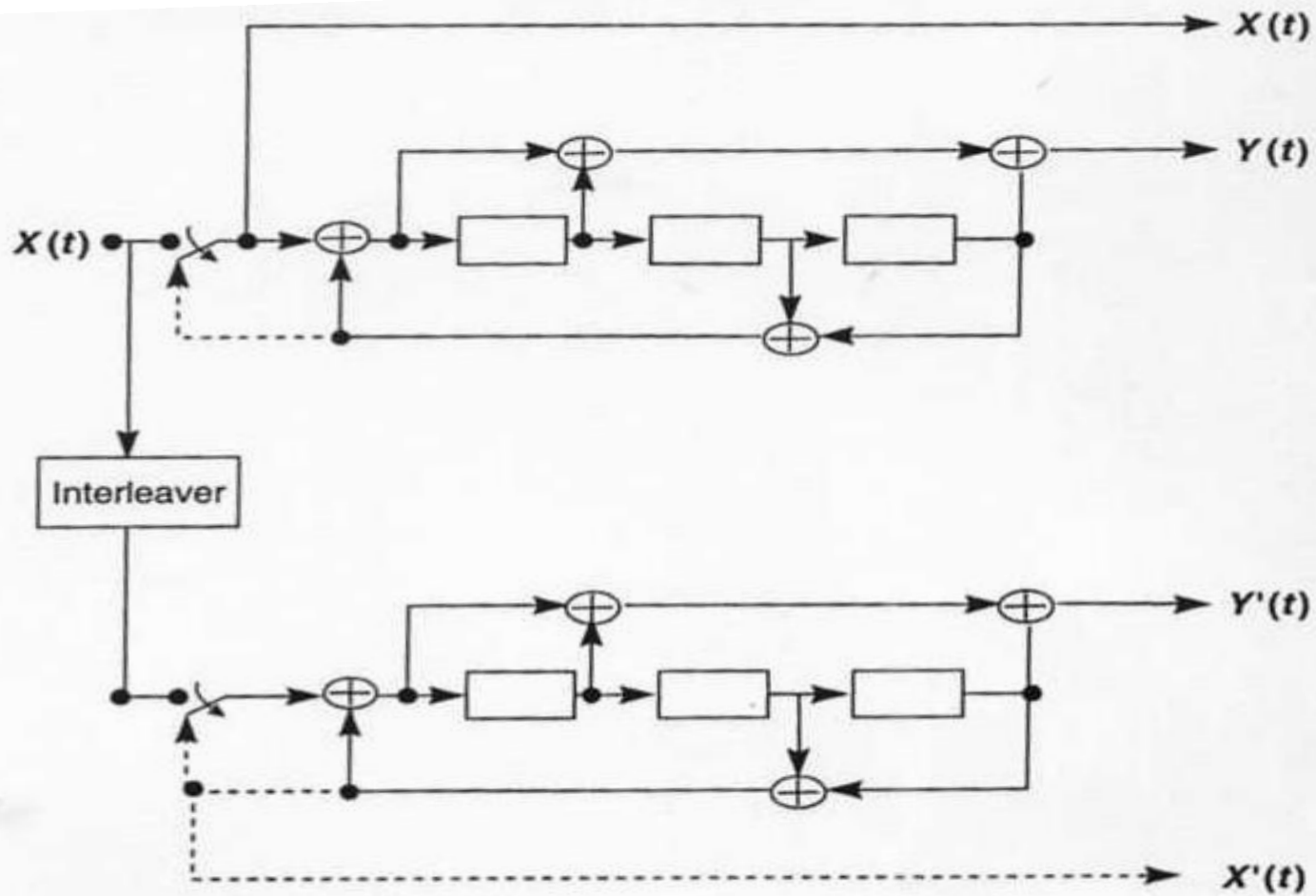
$$L^e(u_k) = \sum_{U+} \beta_k(s) \chi_k(s', s) \alpha_{k-1}(s') / \sum_{U--} \beta_k(s) \chi_k(s', s) \alpha_{k-1}(s') \quad (\text{A-11})$$

**Finally we get**

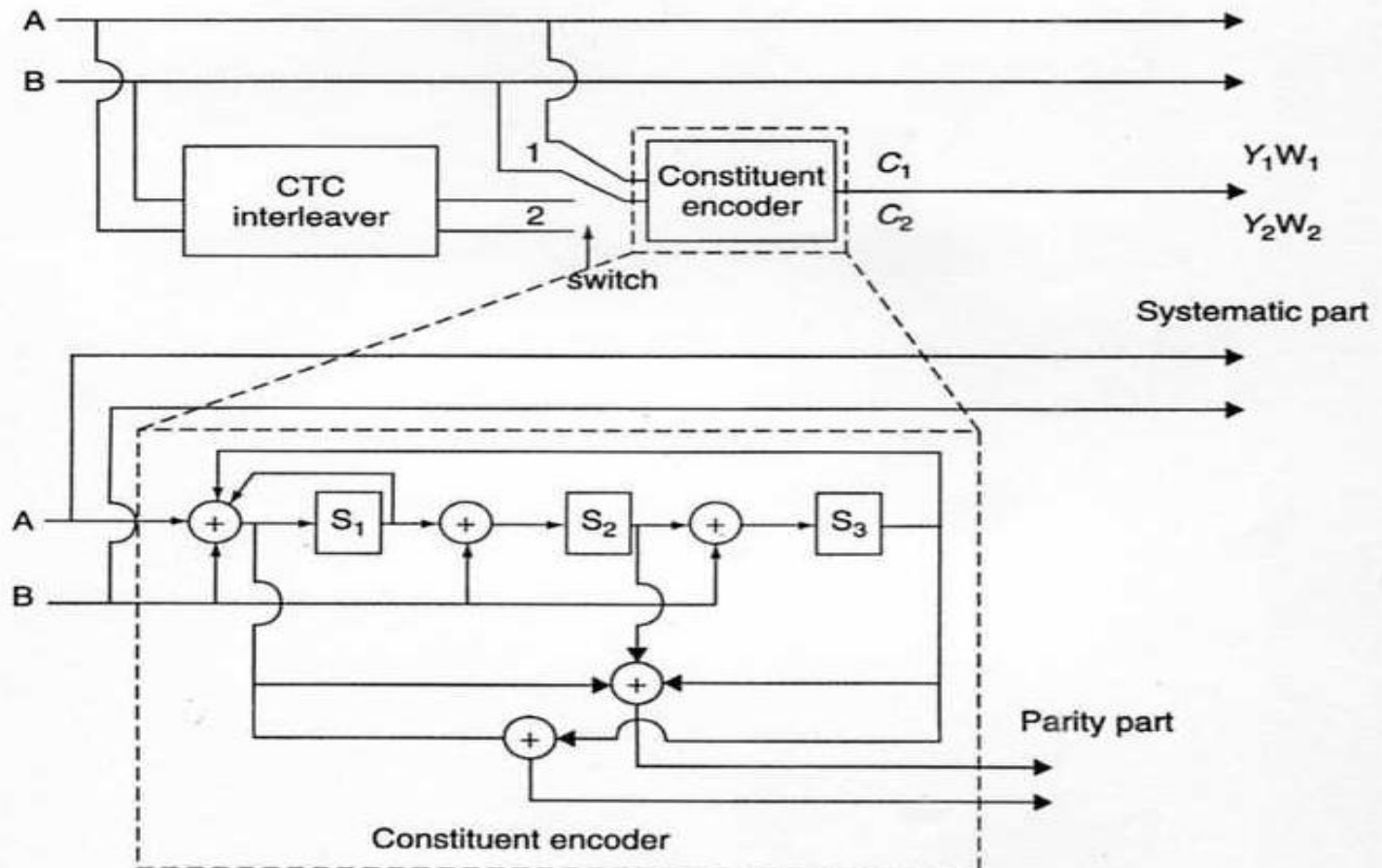
$$L(u_k) = L^a(u_k) + L_c y_{k1} + L^e(u_k) \quad (\text{A-12})$$

# Appendix 7 C : Turbo code in LTE

$$g_2(D) = 1 + D + D^3 \quad g_1(D) = 1 + D^2 + D^3$$







# Turbo code in WiMAX ( IEEE 802.16-e)

