

Department of Electrical Engineering
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ELEG 5693 Wireless Communications

Ch. 5 Equalization

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OUTLINE

- **Introduction**
- **Maximum Likelihood Sequence Estimation (MLSE)**

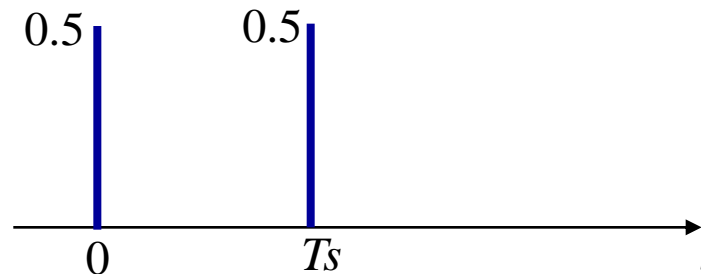
INTRODUCTION

- **Frequency selective fading**

- Frequency domain: Signal bandwidth \gg channel coherence bandwidth
- Time domain: symbol period \ll rms delay spread
 - **Relative arrival time of the multipath components is no longer negligible!**

$$h(t, \tau) = \sum_{l=1}^L h_l(t) \times \delta(\tau - \tau_l)$$

- t : time variation, τ : relative delay between multipath component.
- Power delay profile:
 - The relative power and delay of the multipath component.
 - E.g.



- If the first multipath component arrives at receiver at time 0, then the second multipath component arrives at receiver at time T_s .

INTRODUCTION: ISI

- **Intersymbol interference (ISI)**

- E.g. two resolvable multipath components with relative delay T_s .

- 1st multipath component: $h_0(1), h_0(2), h_0(3), \dots, h_0(k), h_0(k+1), \dots$

- 2nd multipath component: $h_1(1), h_1(2), h_1(3), \dots, h_1(k), h_1(k+1), \dots$

- Tx symbol:

$$x_1, x_2, x_3, \dots, x_k, x_{k+1}, \dots$$

- In the channel

the 1st multipath: $h_0(1)x_1, h_0(2)x_2, h_0(3)x_3, \dots$

the 2nd multipath: $0, h_1(2)x_1, h_1(3)x_2, h_1(4)x_3, \dots,$

- Rx symbols are the combination of the two multipath components

$$y_1 = h_0(1)x_1 + 0 + n_1$$

$$y_2 = h_0(2)x_2 + h_1(2)x_1 + n_2$$

$$y_3 = h_0(3)x_3 + h_1(3)x_2 + n_3$$

$$y_k = h_0(k)x_k + h_1(k)x_{k-1} + n_k$$

AWGN

INTRODUCTION: ISI

- **ISI (Cont'd)**

$$y_k = h_0(k)x_k + h_1(k)x_{k-1} + n_k$$

- The received symbol is a combination of two or more information symbols!
 - x_k : desired symbol. x_{k-1} : **Interference from multipath component.**
- Intersymbol interference:
 - Interference caused by multipath components of frequency selective fading.

- **ISI model**

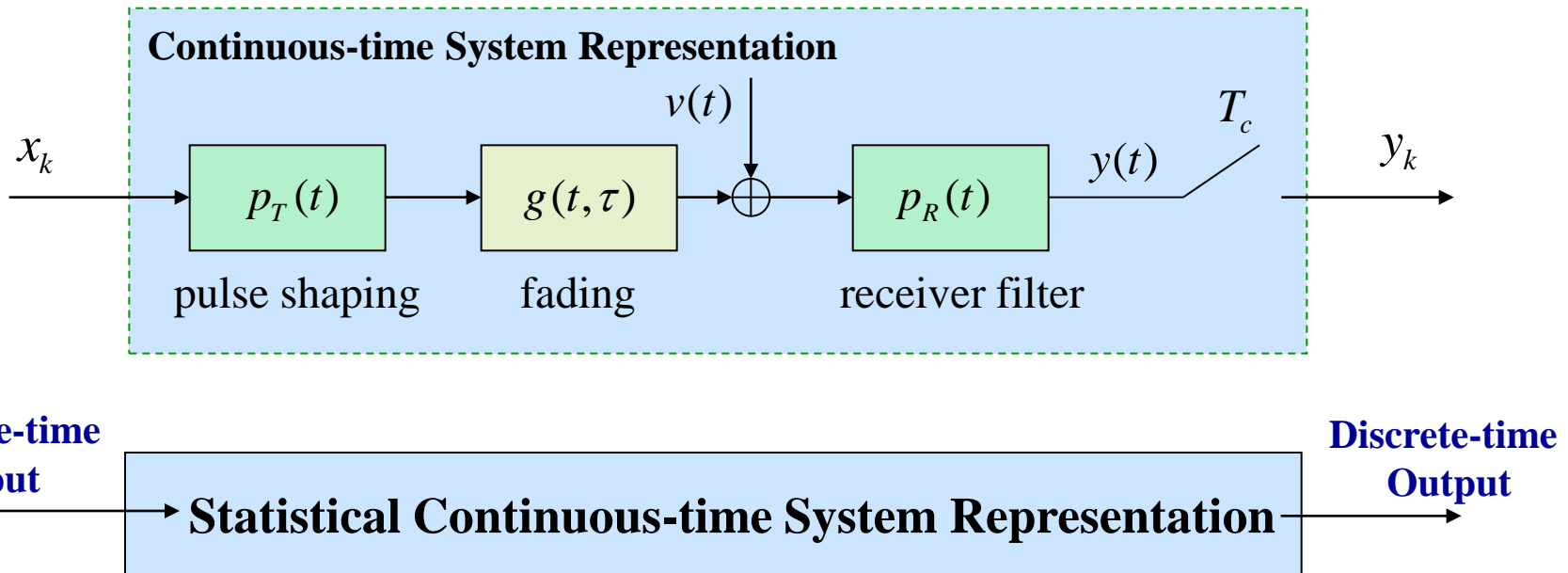
- L resolvable multipath components with relative delay T_s .

$$y_k = h_0(k)x_k + h_1(k)x_{k-1} + \dots + h_{L-1}(k)x_{k-L+1} + n_k$$

$$y_k = \sum_{l=0}^{L-1} h_l(k)x_{k-l} + n_k$$

INTRODUCTION: DISCRETE-TIME MODEL

- What if the relative delay between multipath component is not an integer multiply of symbol period T_s ?
 - Discrete-time model can convert the channel impulse response into desired form
- Discrete-time model



Can we replace the continuous-time system with an equivalent discrete-time system without changing system input-output relationship?

INTRODUCTION: DISCRETE-TIME MODEL

- Composite impulse response

$$h(t, \tau) = p_T(\tau) \otimes g(t, \tau) \otimes p_R(\tau)$$

$$v(t) \otimes p_R(t)$$

– System model

$$x(t) = \sum_{k=-\infty}^{+\infty} x_k \delta(t - kT_s), \quad y(t) = x(t) \otimes h(t, \tau) = \sum_{k=-\infty}^{+\infty} x_k h(t, \tau - kT_s) + n(t)$$

– After sampling

$$y(mT_s) = \sum_{k=-\infty}^{+\infty} x_k h(mT_s, (m-k)T_s) + n(mT_s)$$

– Represent with discrete-time variables

$$h_l(m) = h(mT_s, lT_s)$$

$$y_m = \sum_{k=-\infty}^{+\infty} x_k h_{m-k}(m) + n_m$$

$$y_m = \sum_{l=0}^L h_l(m) x_{k-l} + n_m$$

INTRODUCTION: EQUALIZATION

- **What is equalization?**

- Signal processing operation employed at receiver to mitigate the effects of ISI.
- Adaptive equalization
 - Time-varying frequency-selective fading → Channel impulse response varies with time
 - The equalizer should vary with time as well! → adaptive equalization.

- **A possible equalization method:**

- At time 1, $y_1 = h_0(1)x_1 + 0 + n_1$ (no ISI) → $\hat{x}_1 = y_1 / h_0(1)$
- At time 2, $y_2 = h_0(2)x_2 + h_1(2)x_1 + n_2$ → $\hat{x}_2 = [y_2 - h_1(2)\hat{x}_1] / h_0(2)$
- At time 3, $y_3 = h_0(3)x_3 + h_1(3)x_2 + n_3$ → $\hat{x}_3 = [y_3 - h_1(3)\hat{x}_2] / h_0(3)$

Problem: If \hat{x}_1 is in error, all the remaining symbols will be affected!

Error propagation.

INTRODUCTION: CLASSIFICATION

- **Classification**

- Linear equalization: only linear operations are employed in equalizer.
 - Zero Forcing (ZF), least mean square error (LMS), minimum mean square error (MMSE), etc
 - Advantages: simple
 - Not commonly used in wireless communication system.
- Non-linear equalization:
 - Decision feedback equalization (DFE), **Maximum Likelihood Sequence Estimation (MLSE)**, Delayed Decision Feedback Equalization (DDFE), Reduced State Sequence Estimation (RSSE), Turbo Equalization,
 - More complex than linear equalization
 - Better performance
 - Widely used in wireless communication systems.

- **MLSE is the optimum equalizer**

- It has the best performance among all the equalizers
- It has the highest computational complexity.

OUTLINE

- Introduction
- **Maximum Likelihood Sequence Estimation (MLSE)**

MLSE

- **System model**

- Symbols are transmitted in block (assume N symbols per block)

$$\mathbf{x} = [x_1, x_2, \dots, x_N]$$

- The k th symbol at receiver

$$y_k = \sum_{l=0}^{L-1} h_l(k)x_{k-l} + n_k$$

- n_k is AWGN with variance $\sigma^2 \rightarrow y_k - \sum_{l=0}^{L-1} h_l(k)x_{k-l}$ is Gaussian distributed

$$p(y_k | \mathbf{x}) = p(n_k) = \frac{1}{\pi\sigma^2} \exp\left[-\frac{1}{\sigma^2} \left| y_k - \sum_{l=0}^{L-1} h_l(k)x_{k-l} \right|^2\right]$$

MLSE

- **Likelihood function**

- White noise $\rightarrow n_j$ is independent of $n_i \rightarrow p(n_i, n_j) = p(n_i)p(n_j)$

$$p(y_1, y_2, \dots, y_N | \mathbf{x}) = p(n_1)p(n_2) \times \dots \times p(n_N)$$

$$= \frac{1}{(\pi\sigma^2)^N} \prod_{k=1}^N \exp \left[-\frac{1}{\sigma^2} \left| y_k - \sum_{l=0}^{L-1} h_l(k)x_{k-l} \right|^2 \right]$$

$$= \frac{1}{(\pi\sigma^2)^N} \exp \left[-\frac{1}{\sigma^2} \sum_{k=1}^N \left| y_k - \sum_{l=0}^{L-1} h_l(k)x_{k-l} \right|^2 \right]$$

- **Maximum Likelihood**

- Find $\mathbf{x} = [x_1, x_2, \dots, x_N]$ that maximize $p(y_1, y_2, \dots, y_N | \mathbf{x})$

- Equivalent to: minimize

$$J = \sum_{k=1}^N \left| y_k - \sum_{l=0}^{L-1} h_l(k)x_{k-l} \right|^2$$

MLSE: COST FUNCTION

- **Maximum Likelihood Sequence Estimation**

- Based on the information of the received symbols $\mathbf{y} = [y_1, y_2, \dots, y_N]$ and the channel impulse response, find the sequence $\mathbf{x} = [x_1, x_2, \dots, x_N]$ that minimizes the following cost function

$$J = \sum_{k=1}^N |y_k - r_k|^2$$

$$\text{where } r_k = \sum_{l=0}^{L-1} h_l(k) x_{k-l}$$

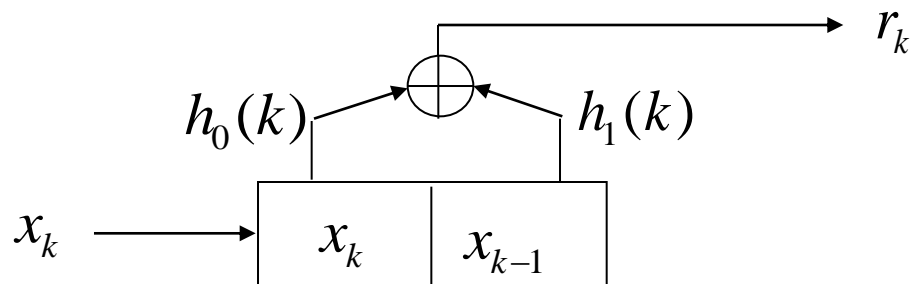
- **Most direct way: exhaustive searching**

- M-ary modulation
 - Modulation constellation size: $M \rightarrow$ each x_k can take one of M possible values.
- N symbols per block
- There are totally possibilities of $\mathbf{x} = [x_1, x_2, \dots, x_N]$
- If $N = 100$, $M = 8$, then we need to search possibilities

MLSE: STATE REPRESENTATION

- State representation of frequency selective fading

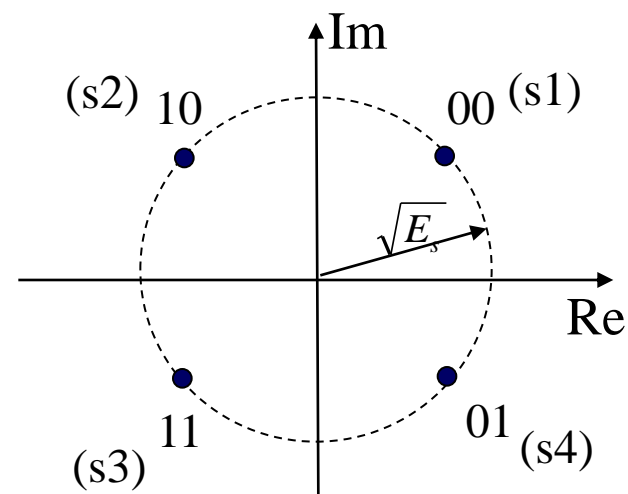
$$y_k = h_0(k)x_k + h_1(k)x_{k-1} + n_k = r_k + n_k$$



Cost function:

$$J = \sum_{k=1}^N |y_k - r_k|^2$$

- E.g. QPSK
 - How many states?



MLSE: STATE REPRESENTATION

- **State representation**

- E.g. QPSK (four symbols: s1, s2, s3, s4), L = 2

- $M^{(L-1)} = 4$ states: a: (s1), b: (s2), c: (s3), d: (s4).

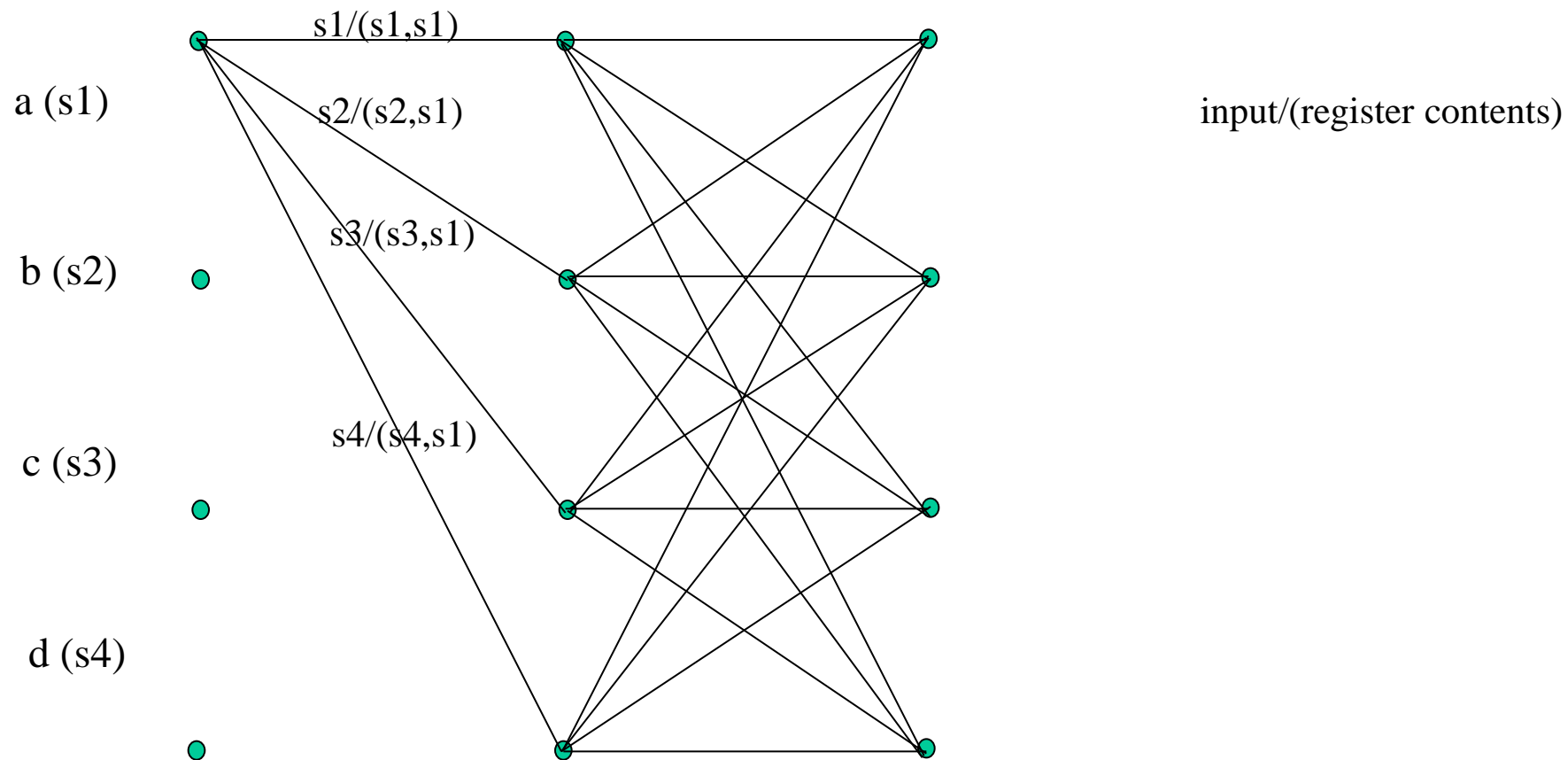
Input	Current state x_{k-1} now	Register contents	Next state x_{k-1} after shift
s1	a (s1)	(s1, s1)	a (s1)
s1	b (s2)	(s1, s2)	a (s1)
s1	c (s3)	(s1, s3)	a (s1)
s1	d (s4)	(s1, s4)	a (s1)
s2	a (s1)	(s1, s1)	b (s2)
s2	b (s2)	(s1, s2)	b (s2)
s2	c (s3)	(s1, s3)	b (s2)
s2	d (s4)	(s1, s4)	b (s2)

MLSE: STATE REPRESENTATION

- State representation

Input	Current state x_{k-1} now	Register contents	Next state x_{k-1} after shift
s3	a (s1)	(s3, s1)	c (s3)
s3	b (s2)	(s3, s2)	c (s3)
s3	c (s3)	(s3, s3)	c (s3)
s3	d (s4)	(s3, s4)	c (s3)
s4	a (s1)	(s4, s1)	d (s4)
s4	b (s2)	(s4, s2)	d (s4)
s4	c (s3)	(s4, s3)	d (s4)
s4	d (s4)	(s4, s4)	d (s4)

MLSE: TRELLIS REPRESENTATION



MLSE: TRELLIS REPRESENTATION

- **Example**

- For a BPSK system with channel length three, how many states do we have? Draw the trellis diagram.

MLSE: VITERBI ALGORITHM

- **Viterbi algorithm**

- Each state transition corresponds to one pair of (x_k, x_{k-1})

- E.g. (state a \rightarrow state c) $\rightarrow (x_k = s3, x_{k-1} = s1)$

- Thus, for each state transition, we can calculate

$$r_k = h_0(k)x_k + h_1(k)x_{k-1}$$

- For each transition, we can find out the Euclidean distance between y_k and r_k

$$J_k = |y_k - r_k|^2 = |y_k - h_0(k)x_k - h_1(k)x_{k-1}|^2$$

- Utilizing the trellis diagram, find out the path with the minimum **accumulated** Euclidean distance

$$J = \sum_{k=1}^N J_k = \sum_{k=1}^N |y_k - r_k|^2$$

MLSE: VITERBI ALGORITHM

- **Example**

- BPSK $s_1 = -1$ $s_2 = 1$

- Channel

$h_0(1)$	$h_0(2)$	$h_0(3)$
$0.3 + 0.5j$	$0.4 + 0.6j$	$0.5 + 0.7j$
$h_1(1)$	$h_1(2)$	$h_1(3)$
$0.8 + 0.4j$	$0.7 + 0.2j$	$0.6 + 0.3j$

- Rx symbols

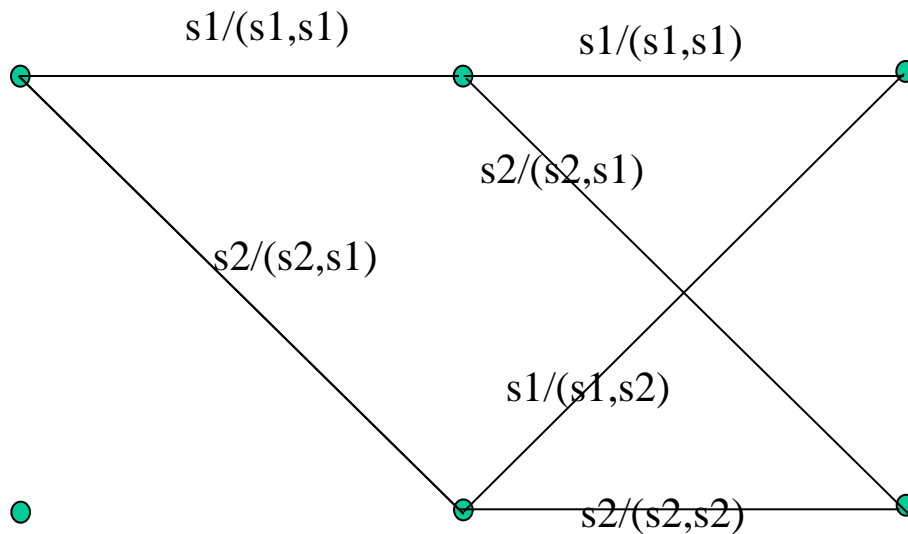
$$\begin{array}{ccc}
 y_1 & y_2 & y_3 \\
 0 - 0.3j & -0.4 + 1.3j & 1.7 + 0.8j
 \end{array}$$

- Using Viterbi algorithm finding out what are the sending symbols x_1 x_2 x_3 ?

MLSE: VITERBI ALGORITHM

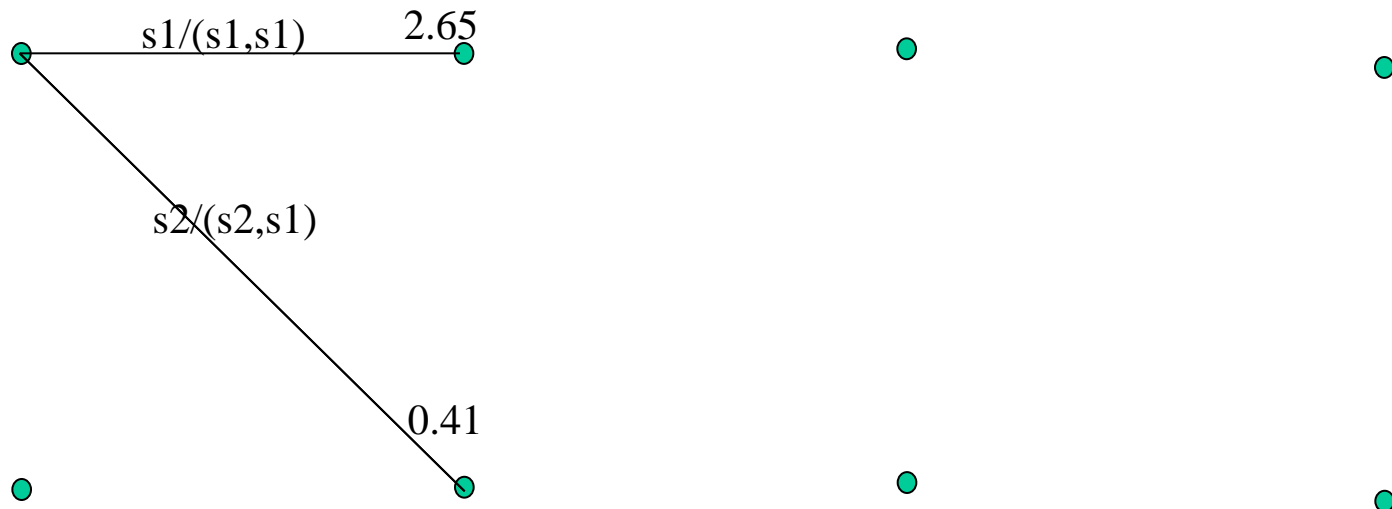
- **Trellis diagram**

- # of states $M^{(L-1)} = 2^{(2-1)} = 2$



MLSE: VITERBI ALGORITHM

\mathbf{h}_0	$0.3 + 0.5j$	$0.4 + 0.6j$	$0.5 + 0.7j$
\mathbf{h}_1	$0.8 + 0.4j$	$0.7 + 0.2j$	$0.6 + 0.3j$
\mathbf{y}	$0 - 0.3j$	$-0.4 + 1.3j$	$1.7 + 0.8j$



$$\mathbf{a}: (s1, s1) \rightarrow r_1 = -1 \cdot h_0 - 1 \cdot h_1 = -1.1 - 0.9j$$

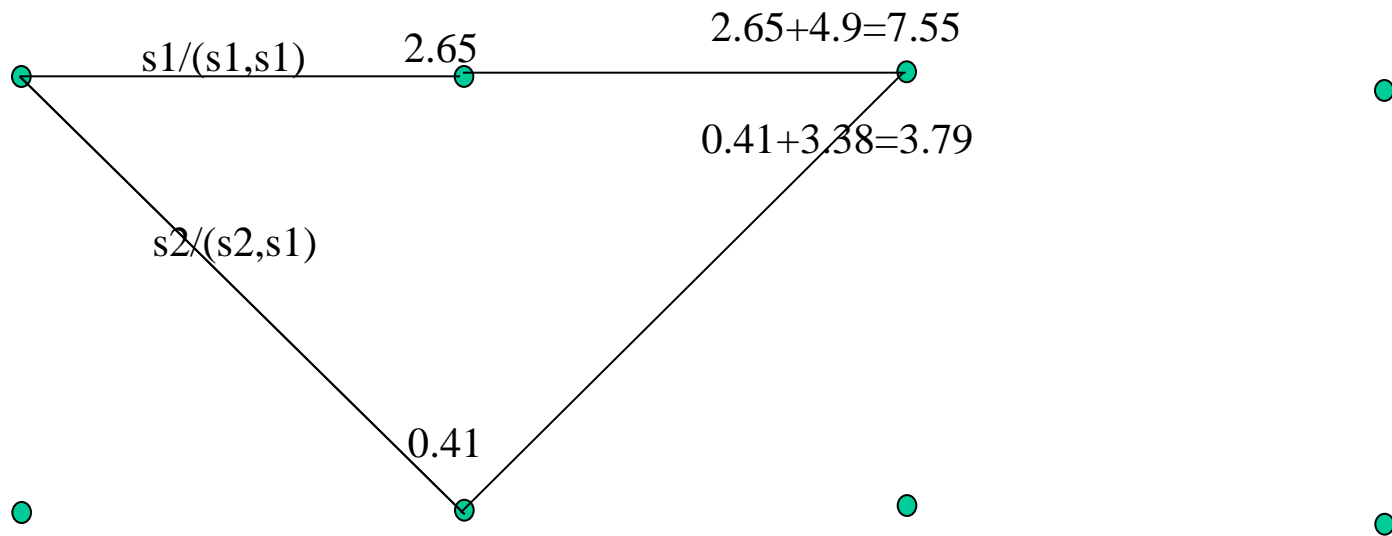
$$J_1 = |y_1 - r_1|^2 = |0 - 0.3j - (-1.1 - 0.9j)|^2 = 2.65$$

$$\mathbf{b}: (s2, s1) \rightarrow r_1 = 1 \cdot h_0 - 1 \cdot h_1 = -0.5 + 0.1j$$

$$J_1 = |y_1 - r_1|^2 = 0.41$$

MLSE: VITERBI ALGORITHM

\mathbf{h}_0	$0.3 + 0.5j$	$0.4 + 0.6j$	$0.5 + 0.7j$
\mathbf{h}_1	$0.8 + 0.4j$	$0.7 + 0.2j$	$0.6 + 0.3j$
\mathbf{y}	$0 - 0.3j$	$-0.4 + 1.3j$	$1.7 + 0.8j$



$$\mathbf{a} \rightarrow \mathbf{a}: (s1, s1) \rightarrow r_1 = -h_0 - h_1 = -1.1 - 0.8j$$

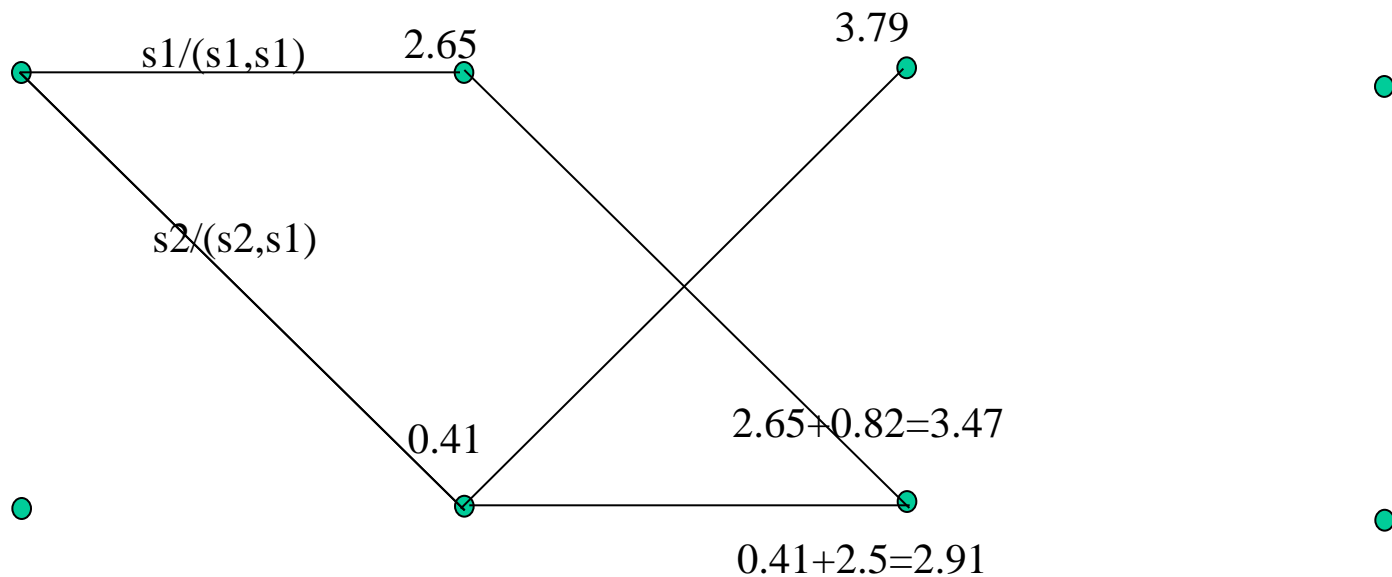
$$J_1 = |y_1 - r_1|^2 = |-0.4 + 1.3j - (-1.1 - 0.8j)|^2 = 4.9$$

$$\mathbf{b} \rightarrow \mathbf{a}: r_1 = -h_0 + h_1 = 0.3 - 0.4j$$

$$J_1 = |-0.4 + 1.3j - (0.3 - 0.4j)|^2 = 3.38$$

MLSE: VITERBI ALGORITHM

h_0	$0.3 + 0.5j$	$0.4 + 0.6j$	$0.5 + 0.7j$
h_1	$0.8 + 0.4j$	$0.7 + 0.2j$	$0.6 + 0.3j$
y	$0 - 0.3j$	$-0.4 + 1.3j$	$1.7 + 0.8j$



$$a \rightarrow b: (s2, s1) \rightarrow r_1 = h_0 - h_1 = -0.3 + 0.4j$$

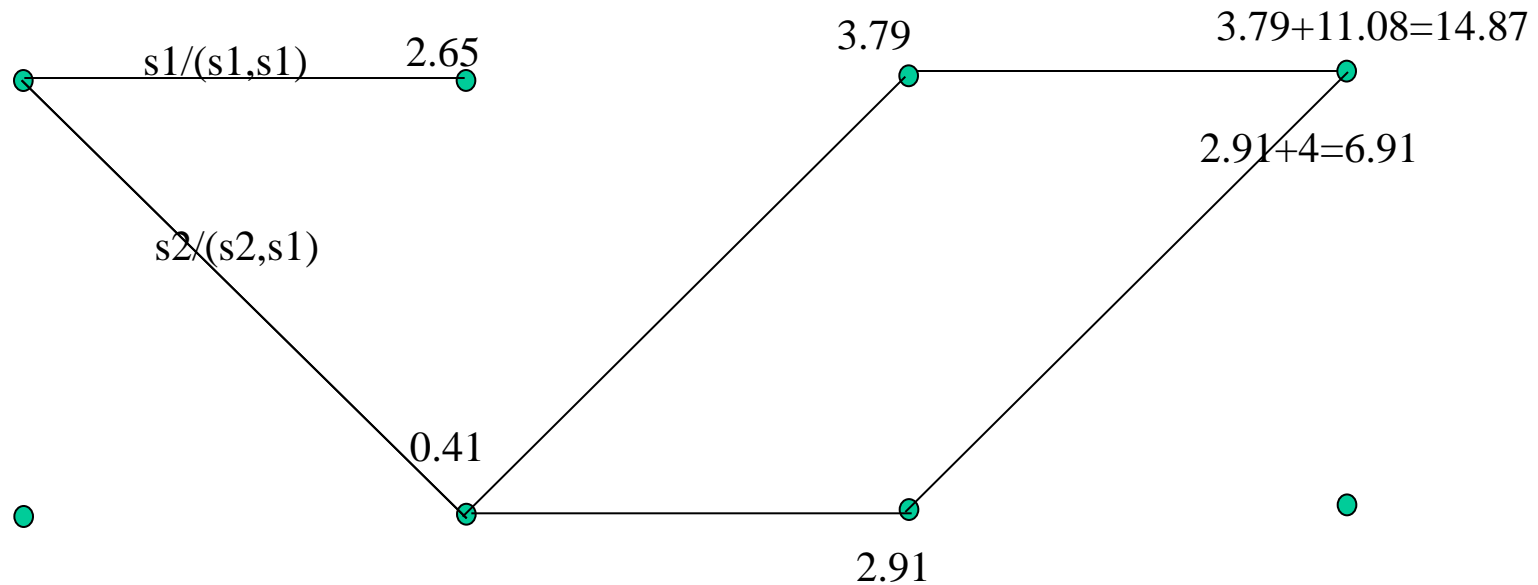
$$J_1 = |y_1 - r_1|^2 = |-0.4 + 1.3j - (-0.3 + 0.4j)|^2 = 0.82$$

$$b \rightarrow a: r_1 = h_0 + h_1 = 1.1 + 0.8j$$

$$J_1 = |-0.4 + 1.3j - (1.1 + 0.8j)|^2 = 2.5$$

MLSE: VITERBI ALGORITHM

h_0	$0.3 + 0.5j$	$0.4 + 0.6j$	$0.5 + 0.7j$
h_1	$0.8 + 0.4j$	$0.7 + 0.2j$	$0.6 + 0.3j$
y	$0 - 0.3j$	$-0.4 + 1.3j$	$1.7 + 0.8j$



$$a \rightarrow b: (s2, s1) \rightarrow r_1 = -h_0 - h_1 = -1.1 - 1.0j$$

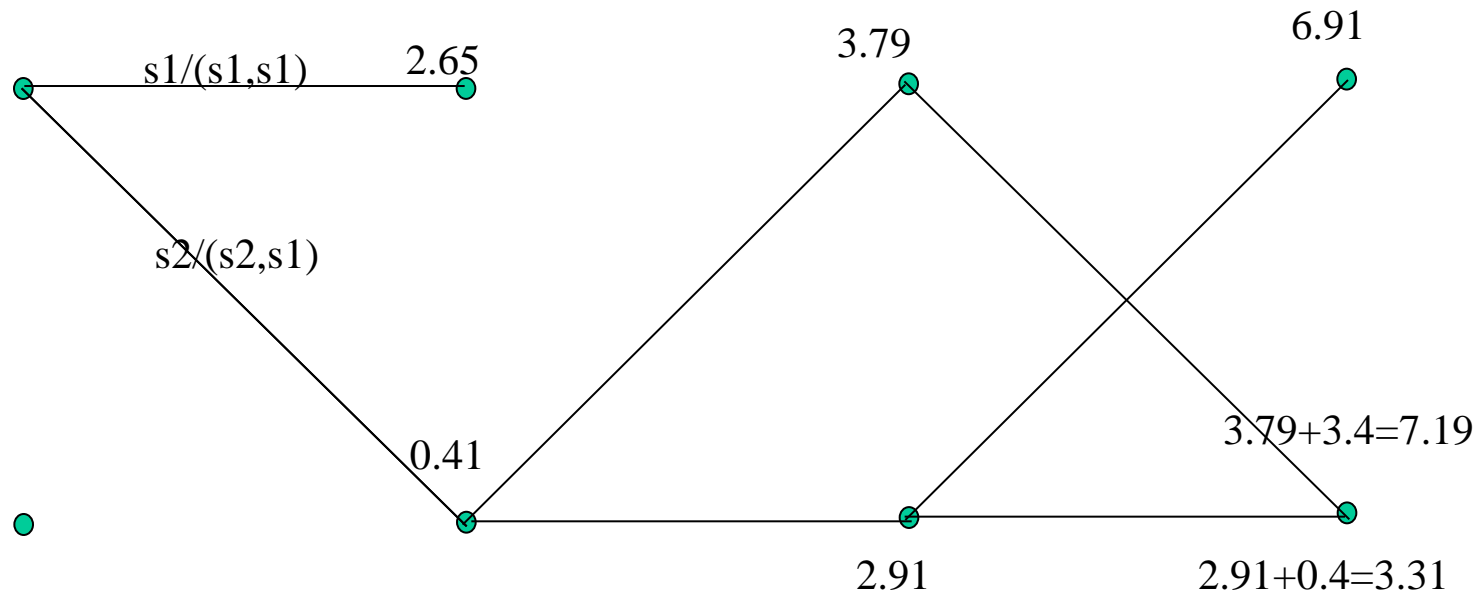
$$J_1 = |y_1 - r_1|^2 = |1.7 + 0.8j - (-1.1 - 1.0j)|^2 = 11.08$$

$$b \rightarrow a: r_1 = -h_0 + h_1 = 0.1 - 0.4j$$

$$J_1 = |1.7 + 0.8j - (0.1 - 0.4j)|^2 = 4$$

MLSE: VITERBI ALGORITHM

h_0	$0.3 + 0.5j$	$0.4 + 0.6j$	$0.5 + 0.7j$
h_1	$0.8 + 0.4j$	$0.7 + 0.2j$	$0.6 + 0.3j$
y	$0 - 0.3j$	$-0.4 + 1.3j$	$1.7 + 0.8j$



$$a \rightarrow b: (s2, s1) \rightarrow r_1 = h_0 - h_1 = -0.1 + 0.4j$$

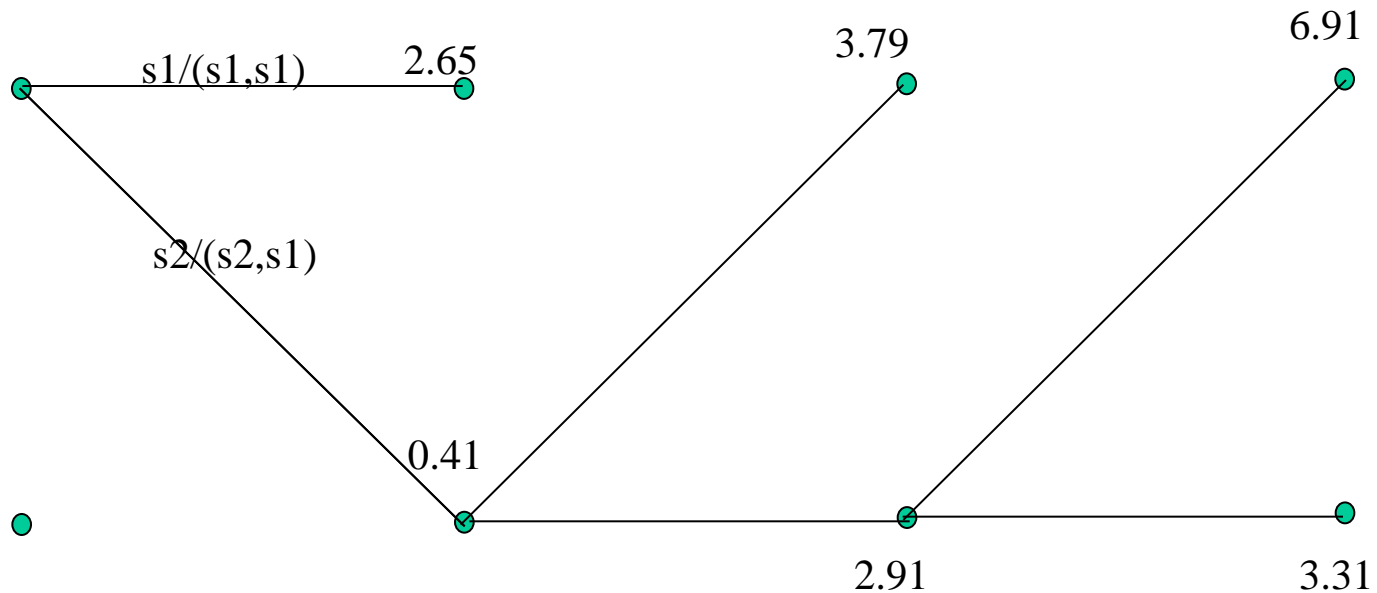
$$b \rightarrow a: r_1 = h_0 + h_1 = 1.1 + 1j$$

$$J_1 = |y_1 - r_1|^2 = |1.7 + 0.8j - (-0.1 + 0.4j)|^2 = 3.4$$

$$J_1 = |1.7 + 0.8j - (1.1 + 1j)|^2 = 0.4$$

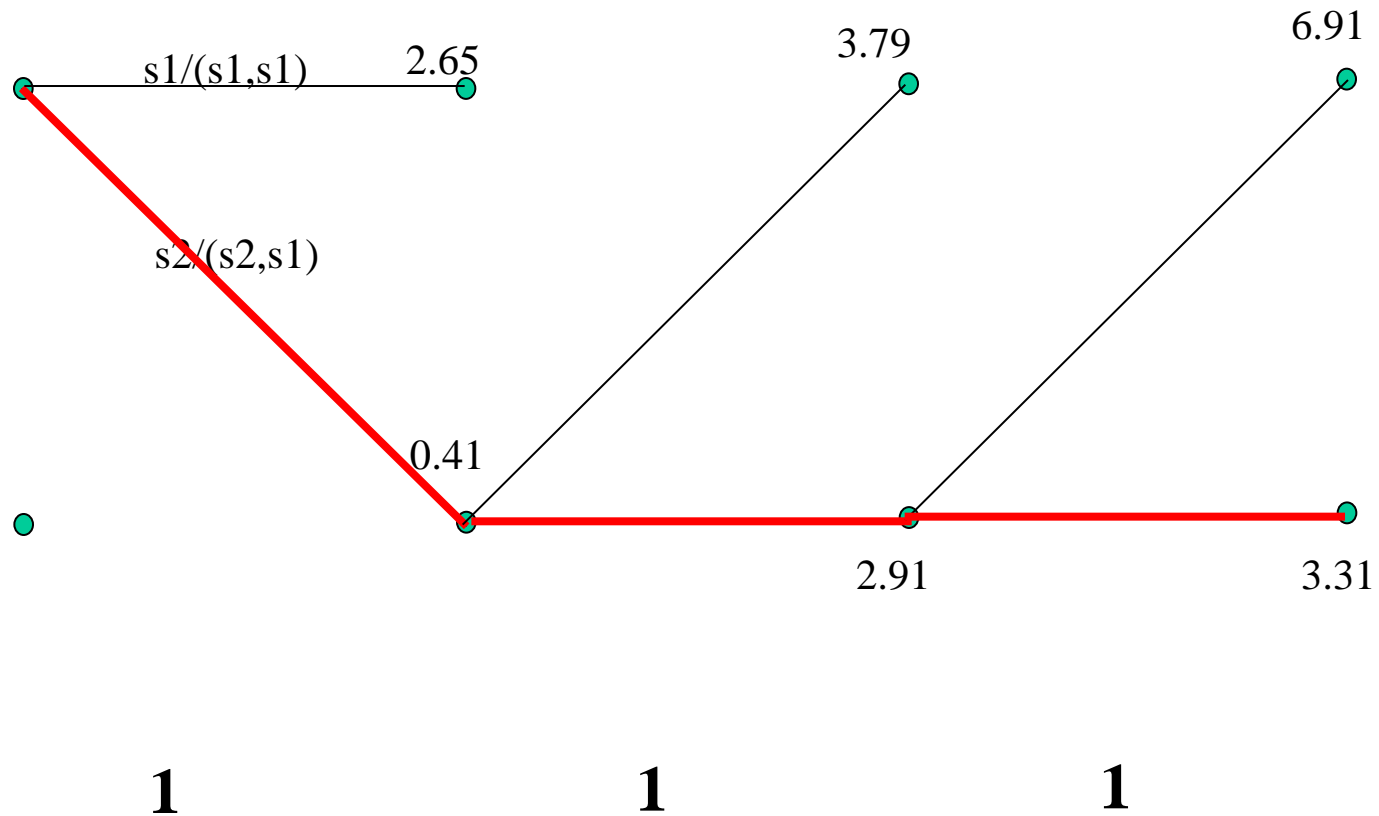
MLSE: VITERBI ALGORITHM

\mathbf{h}_0	$0.3 + 0.5j$	$0.4 + 0.6j$	$0.5 + 0.7j$
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\mathbf{y}	$0 - 0.3j$	$-0.4 + 1.3j$	$1.7 + 0.8j$



MLSE: VITERBI ALGORITHM

\mathbf{h}_0	$0.3+0.5j$	$0.4+0.6j$	$0.5+0.7j$
\mathbf{h}_1	$0.8+0.4j$	$0.7+0.2j$	$0.6+0.3j$
\mathbf{y}	$0-0.3j$	$-0.4+1.3j$	$1.7+0.8j$



MLSE

- **States**
 - $M = 4, L = 3$
 - # of states:
 - $M = 8, L = 2$
 - # of states:
 - $M = 8, L = 3$
 - # of states:
 - $M = 8, L = 4$
 - # of states:

$$\# \text{ of states} = M^{(L-1)}$$