

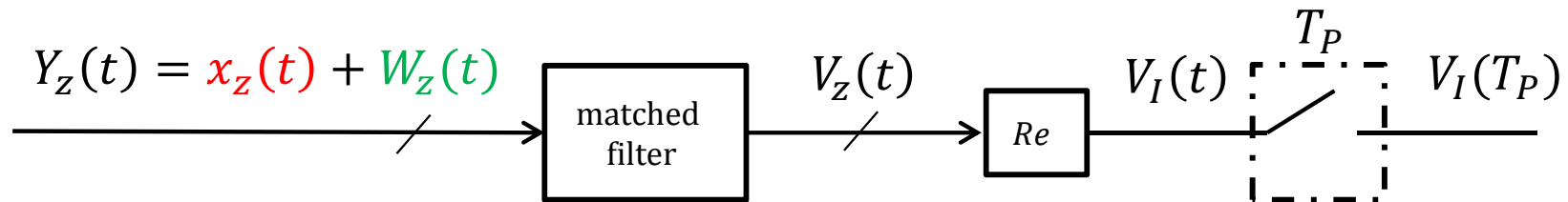
NJIT



New Jersey's Science &
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THE EDGE IN KNOWLEDGE

- Consider now the effect of the matched filter on the sufficient statistics $V_I(T_P)$:



- Recall that we have $V_I(T_P) = m_{0/1} + N_I$

\nearrow
 if $M = 0$

\nwarrow
 if $M = 1$

where $m_{0/1} = \text{Re}\{x_{z,0/1}(t) * h(t) \big|_{t=T_P}\}$

$$N_I \sim N(0, \sigma_{N_I}^2) \quad \text{with} \quad \sigma_{N_I}^2 = \frac{N_0}{2} \int_{-\infty}^{+\infty} |H(f)|^2 df$$

Let's calculate $\sigma_{N_I}^2$ first:

$$\sigma_{N_I}^2 = \frac{N_0}{2} \int_{-\infty}^{+\infty} |H(f)|^2 df$$

$$= \frac{N_0}{2} \int_{-\infty}^{+\infty} |h(t)|^2 dt$$

Rayleigh
theorem

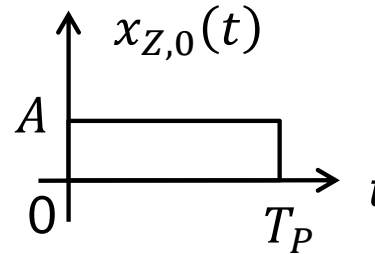
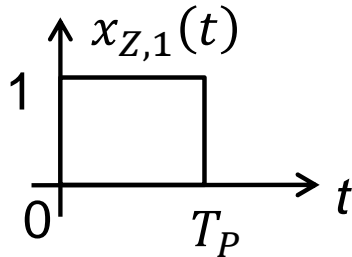
$$= \frac{N_0}{2} \int_{-\infty}^{+\infty} |x_{z,1}^*(-t + T_P) - x_{z,0}^*(-t + T_P)|^2 dt$$

$$= \frac{N_0}{2} \int_{-\infty}^{+\infty} |x_{z,1}(t) - x_{z,0}(t)|^2 dt = \frac{N_0}{2} \Delta_E(1,0)$$

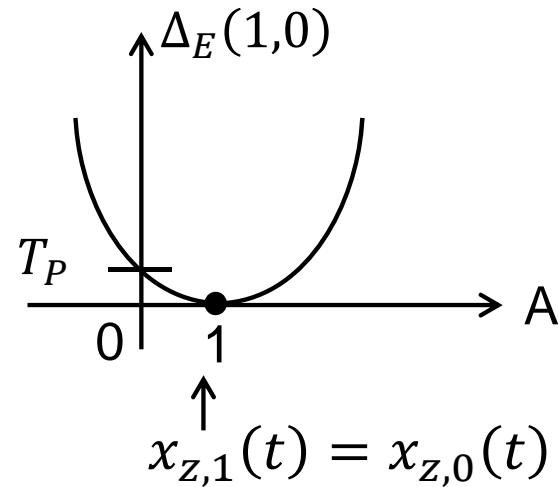
Squared Euclidean distance between
 $x_{z,1}(t)$ and $x_{z,0}(t)$:
 $\Delta_E(1,0)$

- Remark: The Euclidean distance $\Delta_E(1,0)$ measures how “far” $x_{z,1}(t)$ and $x_{z,0}(t)$ are from each other.

Ex.:



$$\begin{aligned}\Delta_E(1,0) &= \int_{-\infty}^{+\infty} |x_{z,1}(t) - x_{z,0}(t)|^2 dt = \int_0^{T_P} (1 - A)^2 dt \\ &= (1 - A)^2 T_P\end{aligned}$$



- Remark: $\Delta_E(1,0) = \Delta_E(0,1)$
- Remark: The squared Euclidean distance can be expressed in terms of the energies E_0 and E_1 and in terms of the correlation coefficient:

$$\rho_{10} = \frac{\int_{-\infty}^{+\infty} x_{z,1}(t) x_{z,0}^*(t) dt}{\sqrt{E_0 E_1}}$$

- In fact:

$$\begin{aligned} \Delta_E(1,0) &= \int_{-\infty}^{+\infty} (x_{z,1}(t) - x_{z,0}(t))^* (x_{z,1}(t) - x_{z,0}(t)) dt \\ &= \int_{-\infty}^{+\infty} |x_{z,1}(t)|^2 dt + \int_{-\infty}^{+\infty} |x_{z,0}(t)|^2 dt - 2 \operatorname{Re} \left\{ \int_{-\infty}^{+\infty} x_{z,1}(t) x_{z,0}^*(t) dt \right\} \\ &= E_1 + E_0 - 2 \sqrt{E_0 E_1} \operatorname{Re}(\rho_{10}) \end{aligned}$$



Ex.: With the waveforms of the previous example, we have:

$$E_1 = T_P, \quad E_0 = A^2 T_P$$

$$\begin{aligned} \rho_{10} &= \frac{\int_{-\infty}^{+\infty} x_{z,1}(t) x_{z,0}^*(t) dt}{\sqrt{E_0 E_1}} \\ &= \frac{\int_0^{T_P} A dt}{\sqrt{A^2 T_P^2}} = \frac{AT_P}{|A|T_P} = \text{sign}(A) = \begin{cases} +1 & \text{if } A > 0 \\ 0 & \text{if } A = 0 \\ -1 & \text{if } A < 0 \end{cases} \end{aligned}$$

$$\begin{aligned} \Rightarrow \Delta_E(1,0) &= E_1 + E_0 - 2\text{sign}(A)\sqrt{E_0 E_1} \\ &= (1 + A^2)T_P - 2AT_P = (1 - A)^2 T_P \end{aligned}$$

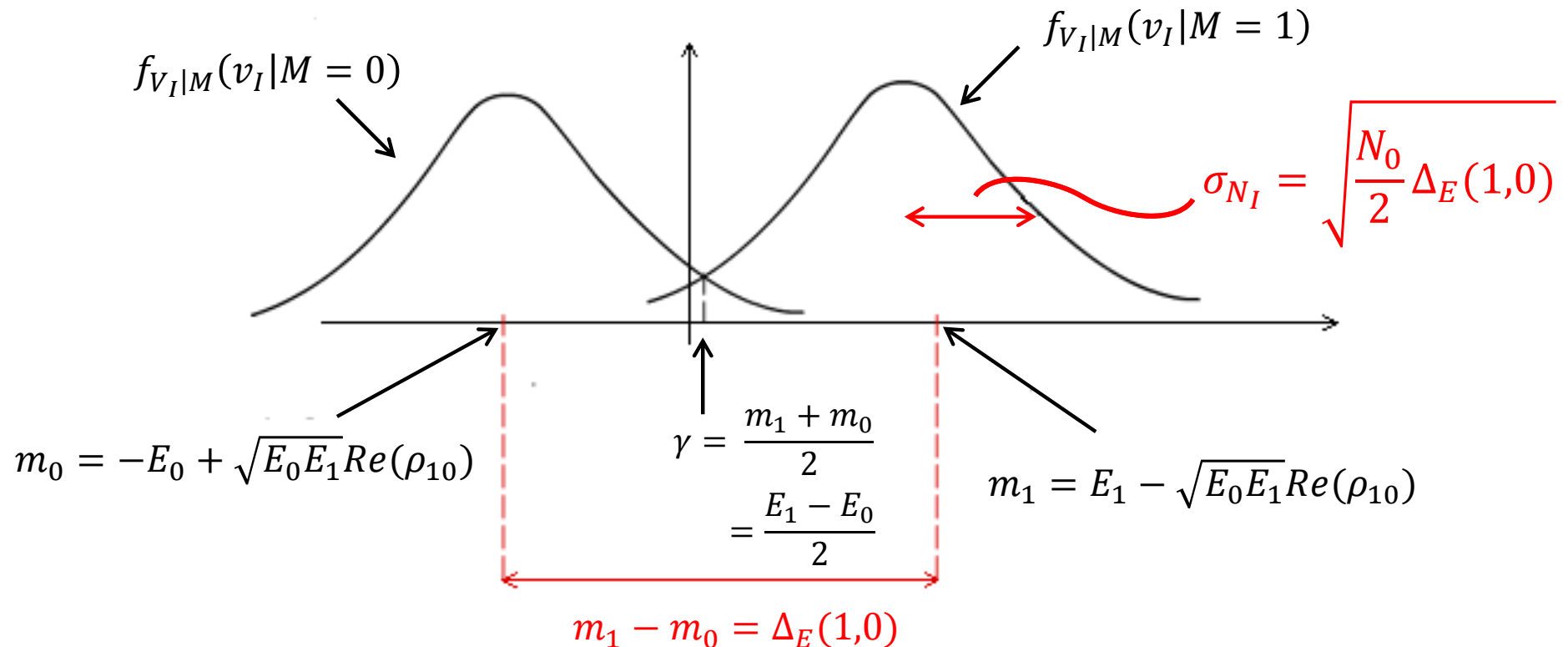


- Using similar calculations, we get

$$m_1 = E_1 - \sqrt{E_0 E_1} \operatorname{Re}(\rho_{10})$$

$$m_0 = -E_0 + \sqrt{E_0 E_1} \operatorname{Re}(\rho_{10})$$

To summarize:



Effective SNR:

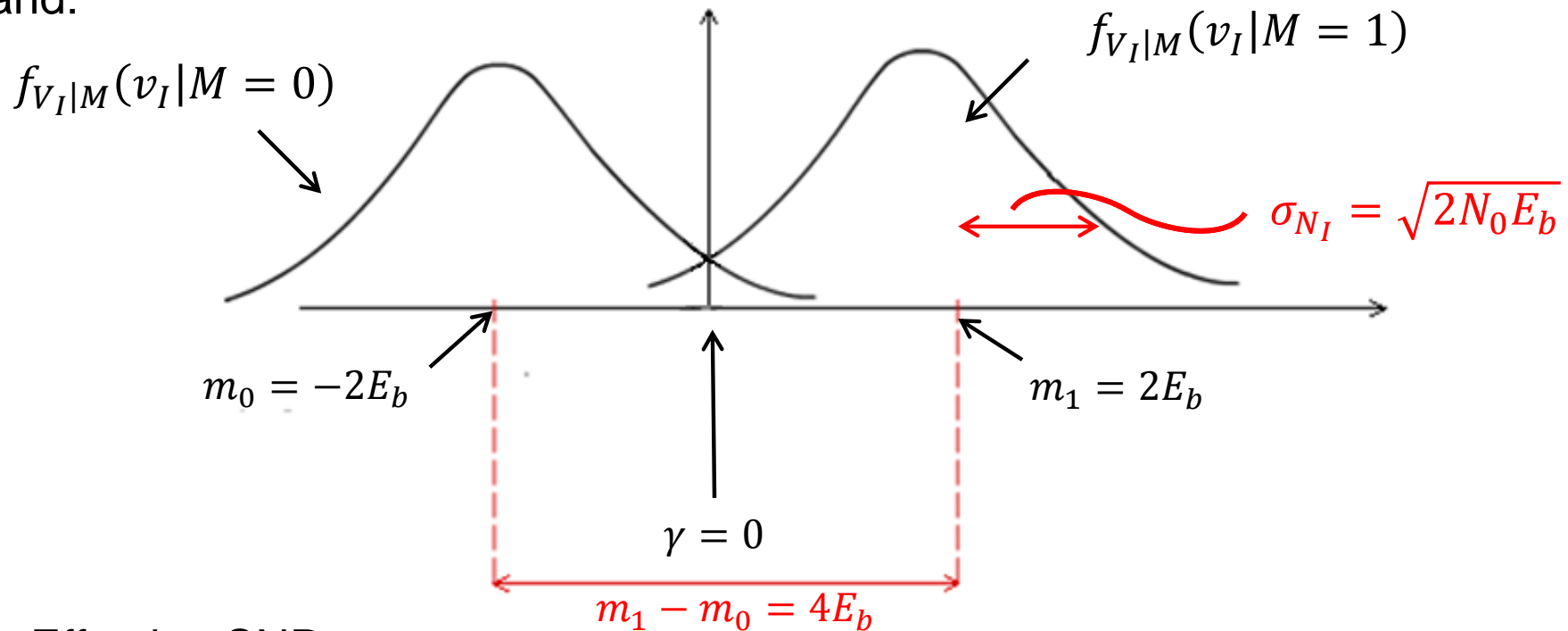
$$\eta = \frac{(m_1 - m_0)^2}{8\sigma_{N_I}^2} = \frac{\Delta_E(1,0)}{4N_0} \quad \leftarrow \text{Increasing } \Delta_E(1,0) \text{ improves } \eta.$$

In the special case in which $x_{z,1}(t) = -x_{z,0}(t)$, we have:

$$E_1 = E_0 = E_b$$

$$\Delta_E(1,0) = 4E_b \text{ (since } \rho_{10} = -1\text{)}$$

and:



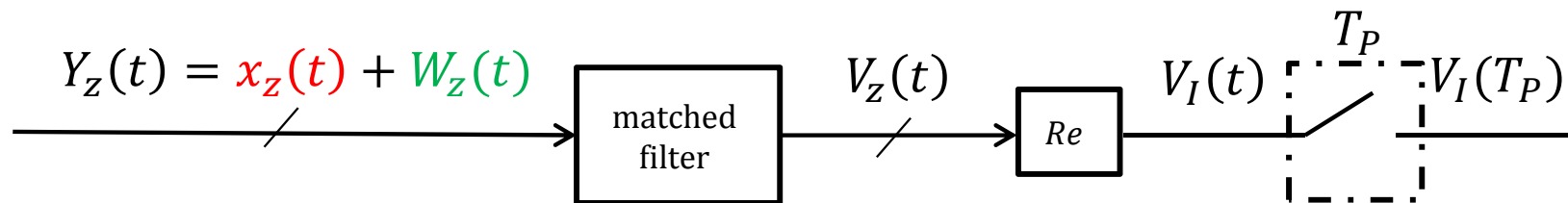
Effective SNR:

$$\eta = \frac{(m_1 - m_0)^2}{8\sigma_{N_I}^2} = \frac{E_b}{N_0}$$

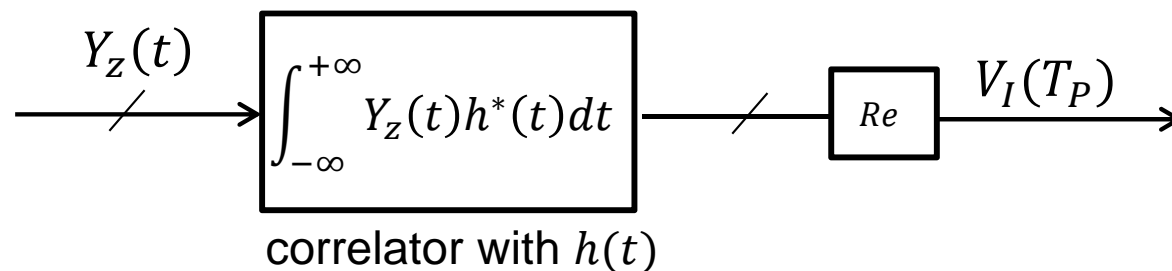
- We have seen that the filter matched to $x_{z,i}(t)$ for $i = 0,1$ can be implemented as a correlator
- Since the matched filter is

$$H(f) = (X_{z,1}^*(f) - X_{z,0}^*(f)) e^{-j2\pi f T_P} \text{ and } h(t) = x_{z,1}^*(-t + T_P) - x_{z,0}^*(-t + T_P)$$

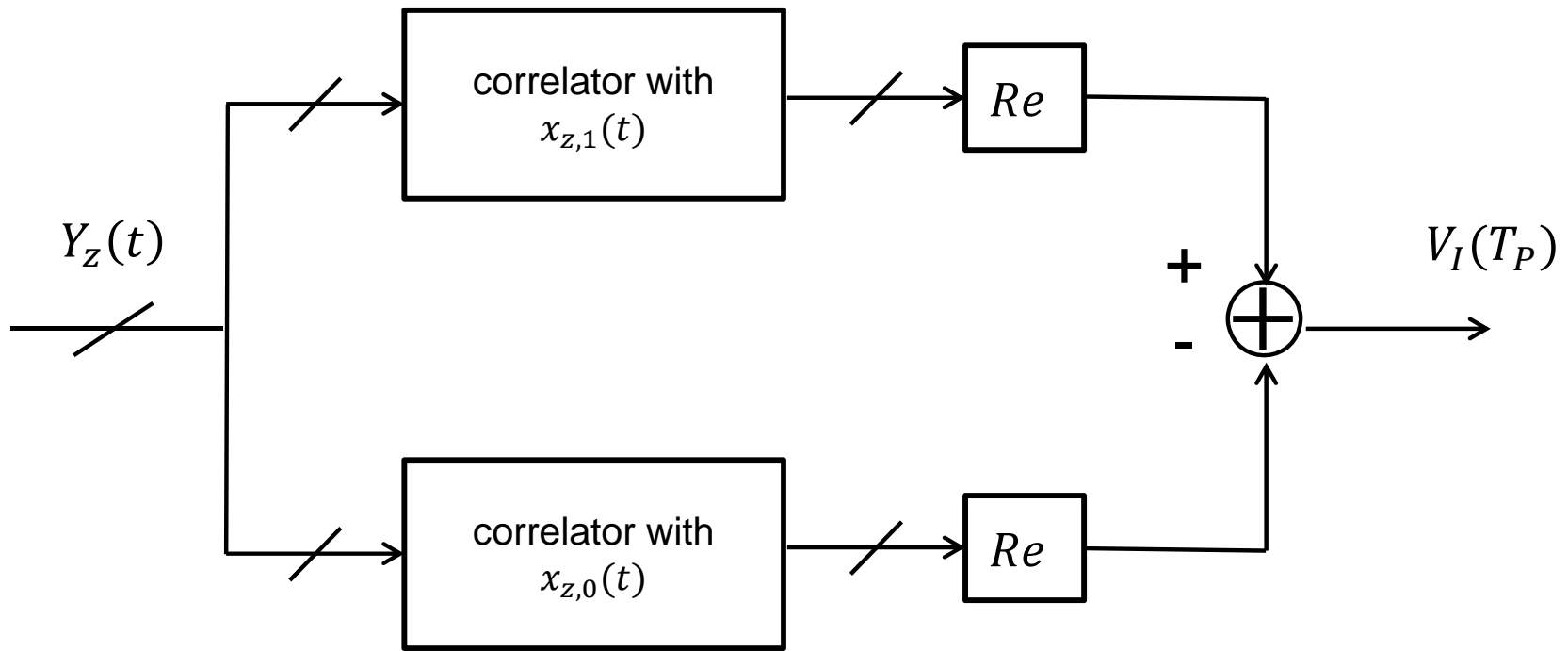
we have that the structure “matched filter + Re + sampler”



is equivalent to the “correlator + Re ” implementation:



Bank of correlators implementation:



- Remark: The correlator + Re implementation is often more convenient, especially for digital signal processing

- Note that

$$V_I(T_P) \underset{\hat{M}=0}{\overset{\hat{M}=1}{>}} \gamma = \frac{E_1 - E_0}{2}$$

is equivalent to

$$V_I(T_P) = \underbrace{\operatorname{Re} \left\{ \int_{-\infty}^{+\infty} Y_Z(t) x_{z,1}^*(t) dt \right\}}_{\text{correlator with } x_{z,1}(t)} - \underbrace{\operatorname{Re} \left\{ \int_{-\infty}^{+\infty} Y_Z(t) x_{z,0}^*(t) dt \right\}}_{\text{correlator with } x_{z,0}(t)} \underset{\hat{M}=0}{\overset{\hat{M}=1}{>}} \gamma$$

which is in turn equivalent to the rule

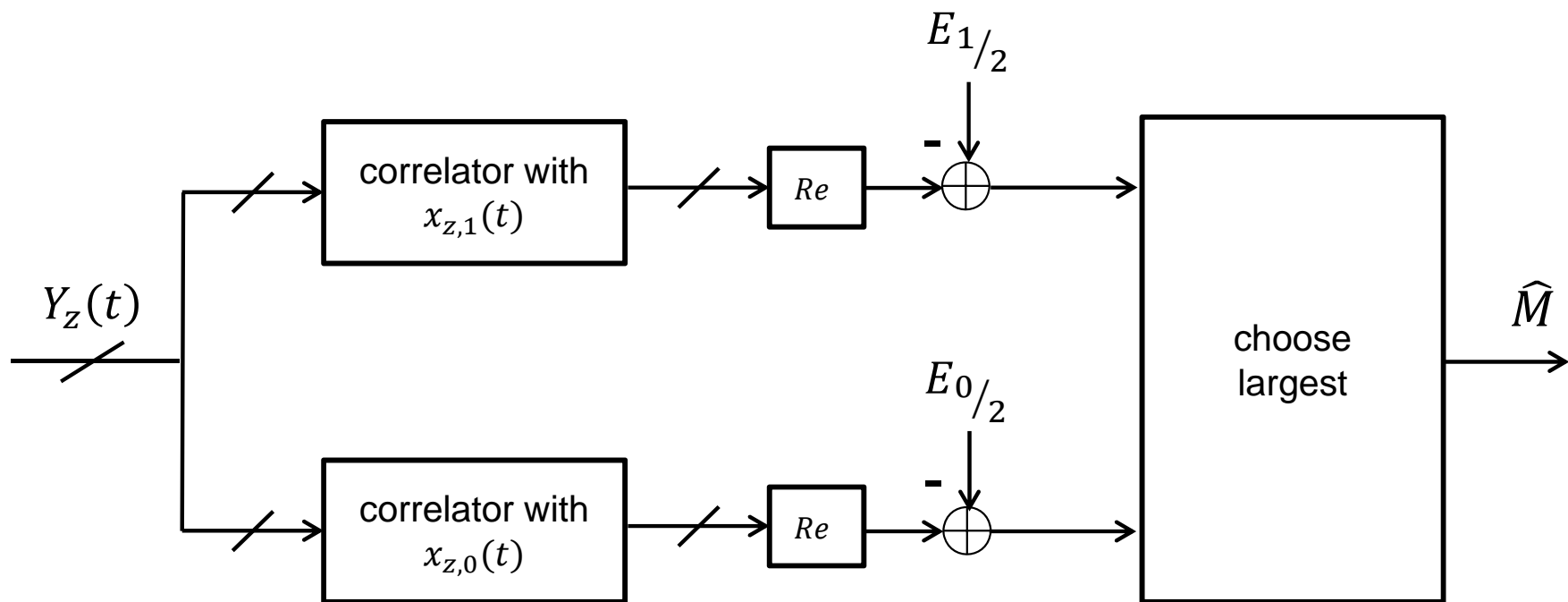
$$T_1 \underset{\hat{M}=0}{\overset{\hat{M}=1}{>}} T_0$$

where

$$T_i = Re \left\{ \int_{-\infty}^{+\infty} Y_z(t) x_{z,i}^*(t) dt \right\} - \frac{E_i}{2}$$

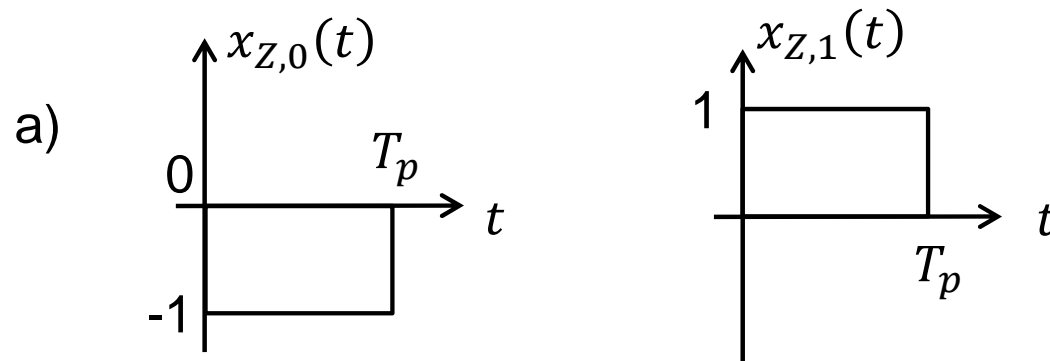
likelihood
metric of
message $i = 0,1$

- The optimal demodulator can then also be expressed in terms of likelihood metrics as

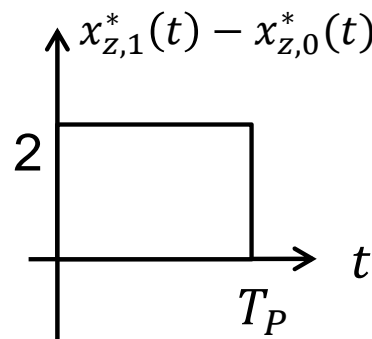


- Remark: This last implementation of the optimal filter will be convenient for the generalization to the transmission of more than one bit.

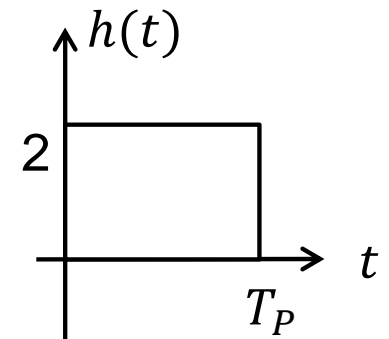
- Ex.: Given the waveforms $\{x_{z,0}(t), x_{z,1}(t)\}$ specified below, calculate the impulse response of the matched filter.



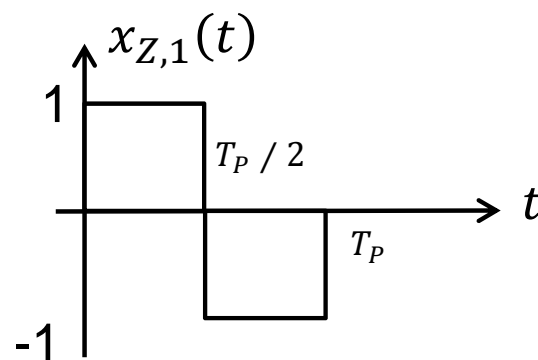
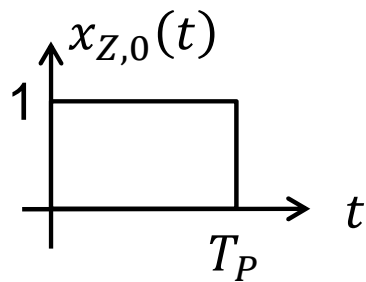
To calculate $h(t) = x_{z,1}^*(-t + T_p) - x_{z,0}^*(-t + T_p)$, let us first evaluate $x_{z,1}^*(t) - x_{z,0}^*(t)$, which is known as the **effective signal**:



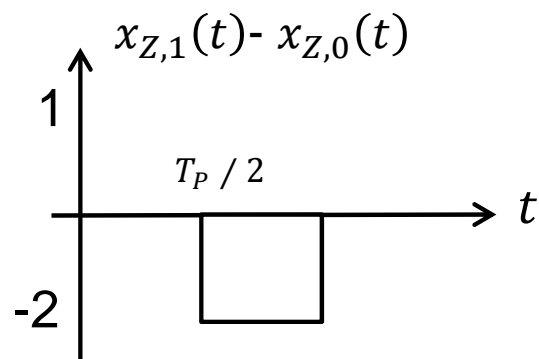
Now, by flipping around the y-axis and delaying by T_p , we get:



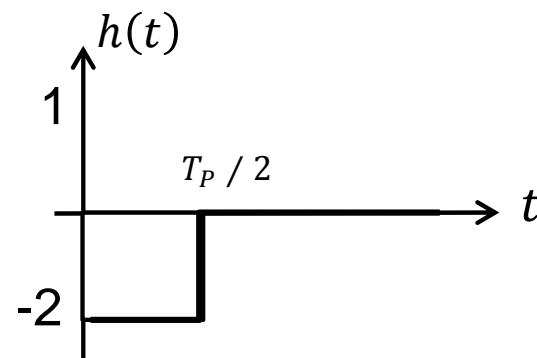
b)



Effective signal:



Matched filter:



- For additional examples, see pp. 13.20 – 13.21



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