Decision and Estimation in Data Processing

Chapter II. Elements of Signal Detection Theory

II.1 Introduction

Introduction

- Signal detection = the problem of deciding which signal is present from 2 or more possibilities
  - one possibility may be that there is no signal
- Based on **noisy** observations
  - signals are affected by noise

The model for signal detection

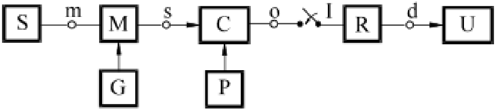

Figure 1: Signal detection model

- Contents:
  - Information source: generates messages a_n with probabilities $p(a_n)$
  - Modulator: transmits a signal $s_n(t)$ for message a_n
  - Channel: adds random noise
  - Sampler: takes samples from the signal $s_n(t)$
  - Receiver: **decides** what message a_n has been transmitted

Practical scenarios

- Data transmission
  - constant voltage levels (e.g. $s_n(t) =$ constant)
  - PSK modulation (Phase Shift Keying): $s_n(t) =$ cosine with same frequency but various initial phase
  - FSK modulation (Frequency Shift Keying): $s_n(t) =$ cosines with different frequencies
  - OFDM modulation (Orthogonal Frequency Division Multiplexing): particular case of FSK
- Radar
  - a signal is emitted; if there is an obstacle, the signal gets reflected back
  - the receiver waits for possible reflections of the signal and must decide
    - no reflection is present -> no object
    - reflected signal is present -> object detected

Generalizations

- Decide between more than two signals
- Number of observations:
  - use only one sample
  - use multiple samples
  - observe the whole continuous signal for some time T

II.2 Detection of constant signals based on 1 sample

Detection of a constant signal, 1 sample

- Simplest case: detection of a constant signal contaminated with white normal noise, using 1 sample
  - two messages a_0 and a_1
  - messages are encoded as constant signals
    - for a_0: send $s_0(t) = 0$
    - for a_1: send $s_1(t) = A$
  - over the signals there is additive noise
  - receiver takes just 1 sample
  - decision: compare sample with a threshold

Threshold-based decision

- The value of the sample taken is $r = s + n$
  - s is the true underlying signal ($s_0 = 0$ or $s_1 = A$)
  - n is a sample of the noise
- n is a (continuous) random variable
- r is a random variable also
  - what distribution does r have compared to n?
- Decision is taken by comparing with a threshold T:
  - if $r < T$, take decision D_0: decide the true signal is s_0
  - if $r \geq T$, take decision D_1: decide the true signal is s_1

Hypotheses

- Receiver chooses between **two hypotheses**:
  - H_0: true signal is s_0 (a_0 has been transmitted)
  - H_1: true signal is s_1 (a_1 has been transmitted)
- Possible results
  1. Correct rejection: no signal present, no signal detected.
     - Decision D_0 when hypothesis is H_0
     - Probability is $P_n = P(D_0 \cap H_0)$
  2. **False alarm**: no signal present, signal detected (error)
     - Decision D_1 when hypothesis is H_0
     - Probability is $P_{fa}P(D_1 \cap H_0)$
  3. **Miss**: signal present, no signal detected (error)
     - Decision D_0 when hypothesis is H_1
     - Probability is $P_m = P(D_0 \cap H_1)$
  4. **Hit**: signal present, signal detected
     - Decision D_1 when hypothesis is H_1
     - Probability is $P_d = P(D_1 \cap H_1)$

Maximum likelihood criterion

- Choose the hypothesis that **seems most likely** given the observed sample r
- The **likelihood** of an observation r = the probability density of r given a hypothesis H_0 or H_1
- Likelihood in case of hypothesis H_0: $w(r|H_0)$
  - r is only noise, so value is taken from the noise distribution
- Likelihood in case of hypothesis H_1: $w(r|H_1)$
  - r is A + noise, so value is taken from the distribution of (A + noise)
- **Likelihood ratio** test:

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

Graphical interpretation

- Consider noise having a normal distribution
- Plot the two density functions for H_0, H_1

Decision via threshold

- Likelihood ratio test for ML = comparing r with a threshold T
- The threshold = the cross-over point of the two distributions

Normal noise

- Particular case: the noise has normal distribution $\mathcal{N}(0, \sigma^2)$
- Likelihood ratio is $\frac{w(r|H_1)}{r|H_0} = \frac{e^{-\frac{(r-A)^2}{2\sigma^2}}}{e^{-\frac{r^2}{2\sigma^2}}} \underset{H_0}{\overset{H_1}{\gtrless}} 1$
- For normal distribution, it is easier to apply *natural logarithm* to the terms
  - logarithm is a monotonic increasing function, so it won't change the comparison
  - if $A < B$, then $\log(A) < \log(B)$
- The **log-likelihood** of an observation = the logarithm of the likelihood value
  - usually the natural logarithm, but any one can be used

Log-likelihood test for ML

- For normal noise, the ML decision means the log-likelihood test

$$\frac{(r-A)^2}{r^2} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

- Applying square root

$$\frac{|r-A|}{|r|} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

- $|r-A| =$ distance from r to A, $|r| =$ distance from r to 0
- ML decision with normal noise: choose the value 0 or A which is **nearest** to r
  - very general principle, encountered in many other scenarios
  - also known as **nearest neighbor** principle / decision
  - ML receiver is also known as **minimum distance receiver**
  - equivalent with setting a threshold $T = \frac{A}{2}$

Generalizations

- What if the noise has another distribution?
  - Threshold T is still the cross-over point, whatever that is
  - There can be more cross-overs, so multiple thresholds
  - Can think that $\mathbb{R}$ axis is split into **decision regions** R_0 and R_1
- What if the noise distributions are different for H_0 and H_1?
  - Threshold T is the cross-over point, whatever that is
- What if the signal $s_0(t)$ (for H_0) is not 0, but another constant value B?
  - T is the crossover point, the distributions are centered on B and A
  - In case of normal noise, choose B or A whichever is nearest (threshold is at middle point)

Generalizations

- What if we have more than two signal levels?
  - e.g. 4 possible signals: -6, -2, 2, 6
  - Just choose the most likely hypothesis, out of 4 likelihood functions
  - Not a single threshold value, now there are more

Exercises

- A signal can have two possible values, 0 or 5. The receiver takes one sample with value $r = 2.25$
  1. Considering that the noise is white gaussian noise, what signal is decided based on the Maximum Likelihood criterion?
  2. What if the signal 0 is affected by gaussian noise $\mathcal{N}(0, 0.5)$, while the signal 5 is affected by uniform noise $\mathcal{U}[-4, 4]$?
  3. Repeat a. and b. assuming the value 0 is replaced by -1
- A signal can have four possible values: -6, -2, 2, 6. Each value lasts for 1 second. The signal is affected by white noise with normal distribution. The receiver takes 1 sample per second. Using ML criterion, decide what signal has been transmitted, if the received samples are:

$$4, 6.6, -5.2, 1.1, 0.3, -1.5, 7, -7, 4.4$$

Computing conditional error probabilities

- We can compute the conditional probabilities of errors
- Consider the decision regions:
  - R_0: when $r \in R_0$, decision is D_0, i.e. (∞, T) for gaussian noise
  - R_1: when $r \in R_1$, decision is D_1, i.e. $[T, \infty)$ for gaussian noise
- Probability of false alarm ***if*** *original signal is* $s_0(t)$

$$P(D_1|H_0) = \int_{R_1} w(r|H_0)dx$$

- Probability of miss ***if*** *original signal is* $s_1(t)$

$$P(D_0|H_1) = \int_{R_0} w(r|H_1)dx$$

- These probabilities do not account for the probability that the signal actually is $s_0(t)$ or $s_1(t)$
  - they are **conditional** ("if")

Computing conditional error probabilities

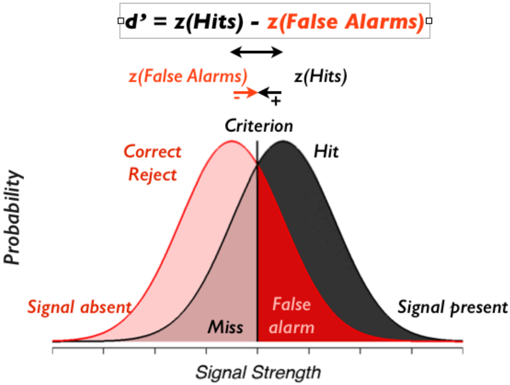

Figure 2: Conditional error probabilities

[image from hhttp://gru.stanford.edu/doku.php/tutorials/sdt]

Reminder: the Bayes rule

- Reminder: the Bayes rule

$$P(A \cap B) = P(B|A) \cdot P(A))$$

- Interpretation
  - The probability $P(A)$ is taken out from $P(B|A)$
  - $P(B|A)$ gives no information on $P(A)$, the chances of A actually happening
  - Example: $\mathrm{P(score \mid shoot)} = \frac{1}{2}$. How many goals are scored?

Exercise

- A signal can have two possible values, 0 or 5. The signal 0 is affected by gaussian noise $\mathcal{N}(0, 0.5)$, while the signal 5 is affected by uniform noise $\mathcal{U}[-4, 4]$. The receiver performs ML decision based on a single sample.
    1. Compute the probability of a wrong decision when the original signal is $s_0(t)$
    2. Compute the probability of a wrong decision when the original signal is $s_1(t)$

Pitfalls of ML decision criterion

- The ML is based on comparing **conditional** probability density functions
  - conditioned by H_0 or by H_1
- Conditioning by H_0 and H_1 ignores the probability of H_0 or H_1 actually happening
  - We don't know how $p(H_0)$ or $P(H_1)$
- If $p(H_0) > p(H_1)$, we may want to move the threshold towards H_1, and vice-versa
  - because it is more likely that the signal is $s_0(t)$
  - and thus we want to "encourage" decision D_0

The minimum error probability criterion

- Takes into account the probabilities $P(H_0)$ and $P(H_1)$
- Goal is to **minimize the total probability of error** P_e
  - errors = false alarms and misses
- We need to find the decision regions R_0 and R_1

Probability of error

- Probability of false alarm

$$\begin{aligned} P(D_1 \cap H_0) =& P(D_1|H_0) \cdot P(H_0) \\ =& \int_{R_1} w(r|H_0)dx \cdot P(H_0) \\ =& (1 - \int_{R_0} w(r|H_0)dx \cdot P(H_0) \end{aligned}$$

- Probability of miss

$$\begin{aligned} P(D_0 \cap H_1) =& P(D_0|H_1) \cdot P(H_1) \\ =& \int_{R_0} w(r|H_1)dx \cdot P(H_1) \end{aligned}$$

- The sum is

$$P_e = P(H_0) + \int_{R_0} [w(r|H_1) \cdot P(H_1) - w(r|H_0) \cdot P(H_0)]dx$$

Minimum probability of error

- We want to minimize P_e, i.e. to minimize the integral
- To minimize the integral, we choose R_0 such that for all $r \in R_0$, the term inside the integral is **negative**
  - because integrating over all the interval where the function is negative ensures minimum value of integral
- So, when $w(r|H_1) \cdot P(H_1) - w(r|H_0) \cdot P(H_0) < 0$ we have $r \in R_0$, i.e. decision D_0
- Conversely, when $w(r|H_1) \cdot P(H_1) - w(r|H_0) \cdot P(H_0) > 0$ we have $r \in R_1$, i.e. decision D_1
- Therefore

$$w(r|H_1) \cdot P(H_1) - w(r|H_0) \cdot P(H_0) \underset{H_0}{\overset{H_1}{\gtrless}} 0$$

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P(H_0)}{P(H_1)}$$

Interpretation

- Similar to ML, but threshold depends on probabilities of the two hypotheses
  - When one hypotheses is more likely than the other, the threshold is pushed in its favor, towards the other
- Also based on a **likelihood ratio** test, just like ML

Minimum probability of error - gaussian noise

- Assuming the noise is gaussian (normal), $\mathcal{N}(0, \sigma^2)$

$$w(r|H_1) = e^{-\frac{(r-A)^2}{2\sigma^2}}$$

$$w(r|H_0) = e^{-\frac{r^2}{2\sigma^2}}$$

- Apply natural logarithm

$$-\frac{(r-A)^2}{2\sigma^2} + \frac{r^2}{2\sigma^2} \underset{H_0}{\overset{H_1}{\gtrless}} \ln\left(\frac{P(H_0)}{P(H_1)}\right)$$

- Equivalently

$$2rA - A^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \cdot \ln\left(\frac{P(H_0)}{P(H_1)}\right)$$

$$r \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{\frac{A^2 + 2\sigma^2 \cdot \ln\left(\frac{P(H_0)}{P(H_1)}\right)}{2A}}_{T}$$

Decision regions

- We still compare with a threshold T, but its value is shifted towards the less probable hypothesis
  - T depends on the ratio $\frac{P(H_0)}{P(H_1)}$
- Decision regions
  - $R_0 = (-\infty, T]$
  - $R_1 = [T, \infty)$
  - will be different for other noise distributions (non-gaussian)

Exercises

- An information source provides two messages with probabilities $p(a_0) = \frac{2}{3}$ and $p(a_1) = \frac{1}{3}$. The messages are encoded as constant signals with values -5 (a_0) and 5 (a_1). The signals are affected by gaussian noise $\mathcal{N}(0, \sigma^2 = 1)$ The receiver takes one sample r. Decision is done by comparing r with a threshold value T, as follows: if $r < T$ it is decided that the transmitted message is a_0, otherwise it is a_1.
  1. Find the threshold value T according to the minimum probability of error criterion
  2. What if the signal 5 is affected by uniform noise $\mathcal{U}[-4, 4]$?
  3. What are the probabilities of false alarm and of miss?

Minimum risk (cost) criterion

- What if we care more about one type of errors (e.g. false alarms) than other kind (e.g. miss)?
- Minimum risk (cost) criterion: assign costs to decisions, minimize average cost
  - C_{ij} = cost of decision D_i when true hypothesis was H_j
  - C_{00} = cost for good detection D_0 in case of H_0
  - C_{10} = cost for false alarm (detection D_1 in case of H_0)
  - C_{01} = cost for miss (detection D_0 in case of H_1)
  - C_{11} = cost for good detection D_1 in case of H_1
- The risk = the average cost

$$R = C_{00}P(D_0 \cap H_0) + C_{10}P(D_1 \cap H_0) + C_{01}P(D_0 \cap H_1) + C_{11}P(D_1 \cap H_1)$$

- Minimum risk criterion: **minimize the risk R**

Computations

- Proof on table:
  - Use Bayes rule
  - Notations: $w(r|H_j)$ (*likelihood*)
  - Probabilities: $\int_{R_i} w(r|H_j) dV$
- Conclusion, **decision rule is**

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{(C_{10} - C_{00}) p(H_0)}{(C_{01} - C_{11}) p(H_1)}$$

Interpretation

- Similar to ML and to minimum probability of error criteria
  - also uses a **likelihood ratio** test
- Both probabilities and the assigned costs can move threshold towards one side or the other
- If $C_{10} - C_{00} = C_{01} - C_{11}$, reduces to previous criterion (minimum probability of error)
  - e.g. if $C_{00} = C_{11} = 0$, and $C_{10} = C_{01}$

In gaussian noise

- If the noise is gaussian (normal), then similar to other criteria, apply logarithm
- Equivalently

$$-(r-A)^2 + r^2 \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{2\sigma^2 \cdot \ln\left(\frac{(C_{10}-C_{00})p(H_0)}{(C_{01}-C_{11})p(H_1)}\right)}_{C}$$

$$r \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{\frac{A^2 + 2\sigma^2 \cdot \ln\left(\frac{(C_{10}-C_{00})p(H_0)}{(C_{01}-C_{11})p(H_1)}\right)}{2A}}_{T}$$

In gaussian noise

- In general, for likelihood ratio test $\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} K$, the threshold is

$$T = \frac{A^2 + 2\sigma^2 \cdot \ln K}{2A}$$

Example

- Example at blackboard: 0 / 5, random noise with $N(0, \sigma^2)$, one sample

Neymar-Pearson criterion

- Neymar-Pearson criterion: maximize probability of a hit $(P(D_1 \cap H_1))$ while keeping probability of false alarms smaller then a limit $(P(D_1 \cap H_0) \leq \lambda)$
- Deduce the threshold T from the limit condition $P(D_1 \cap H_0) = \lambda$

Exercise

- An information source provides two messages with probabilities $p(a_0) = \frac{2}{3}$ and $p(a_1) = \frac{1}{3}$.
- The messages are encoded as constant signals with values -5 (a_0) and 5 (a_1).
- The signals are affected by noise with triangular distribution $[-5, 5]$.
- The receiver takes one sample r.
- Decision is done by comparing r with a threshold value T, as follows: if $r < T$ it is decided that the transmitted message is a_0, otherwise it is a_1.
    1. Find the threshold value T according to the Neymar-Pearson criterion, considering $P_{fa} \leq 10^{-2}$
    2. What is the probability of hit?

Two non-zero levels

- What if the s_0 signal is not 0, but another constant signal $s_0 = B$?
- Noise distribution $w(r|H_0)$ is centered on B, not 0
- Otherwise, everything else stays the same
- Performance is defined by the gap between the two levels $(A - B)$
  - same performance if $s_0 = 0$, $s_1 = A$ or if $s_0 = -\frac{A}{2}$ and $s_1 = \frac{A}{2}$
- Valid for all decision criteria

Differential vs single-ended signalling

- Single-ended signaling: one signal is 0, other is non-zero
  - $s_0 = 0$, $s_1 = A$
- Differential signaling: use two non-zero levels with different sign, same absolute value
  - $s_0 = -\frac{A}{2}$, $s_1 = \frac{A}{2}$
- Which is better?

Differential vs single-ended signalling

- If gap difference between levels is the same, performance is the same
- Average power of a signal = average squared value
- For differential signal: $P = \left(\pm\frac{A}{2}\right)^2 = \frac{A^2}{4}$
- For signal ended signal: $P = P(H_0) \cdot 0 + P(H_1)\,(A)^2 = \frac{A^2}{2}$
  - assuming equal probabilities $P(H_0) = P(H_1) = \frac{1}{2}$
- Differential uses half the power of single-ended (i.e. better)

Summary of criteria

- We have seen decision based on 1 sample r, between 2 constant levels
- All decisions are based on a likelihood-ratio test

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- Different criteria differ in the chosen value of K (likelihood threshold)
- Depending on the noise distributions, the real axis is partitioned into regions
  - region R_0: if r is in here, decide D_0
  - region R_1: if r is in here, decide D_1
  - e.g. $R_0 = (-\infty, \frac{A+B}{2}]$, $R_1 = (\frac{A+B}{2}, \infty)$ (ML)
- For gaussian noise, the threshold is $T = \frac{A^2 + 2\sigma^2 \cdot \ln K}{2A}$

Receiver Operating Characteristic

- The receiver performance is usually represented with **"Receiver Operating Characteristic" (ROC)** graph
- It is a graph of hit probability $P_d = P(D_1 \cap H_1)$ (correct detection) as a function of false alarm probability $P_{fa} = P(D_1 \cap H_0)$

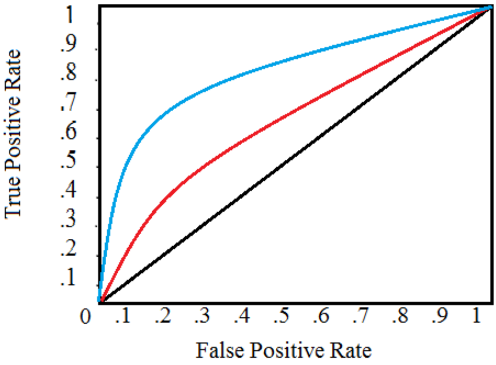

Figure 3: Sample ROC curves

Receiver Operating Characteristic

- There is always a **tradeoff** between good P_d and bad P_{fa}
  - to increase P_d one must also increase P_{fa}
  - if we want to make sure we don't miss any real detections (increase P_d), we pay by increasing the chances of false alarms
- Different criteria = different likelihood thresholds K = different points on the graph = different tradeoffs
  - but the tradeoff cannot be avoided
- How to improve the receiver?
  - i.e. increase P_D while keeping P_{fa} the same

Performance of likelihood-ratio decoding in WGN

- WGN = "White Gaussian Noise"
- Assume equal probabilities $P(H_0) = P(H_1) = \frac{1}{2}$
- All decisions are based on a likelihood-ratio test

$$\frac{w(r|H_1)}{w(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- Hit probability is

$$\begin{aligned}
P_{hit} =& P(D_1|H_1)P(H_1) \\
=& P(H_1)\int_T^{\infty} w(r|H_1) \\
=& P(H_1)(F(\infty) - F(T)) \\
=& \frac{1}{4}\left(1 - erf\left(\frac{T-A}{\sqrt{2}\sigma}\right)\right) \\
=& Q\left(\frac{T-A}{\sqrt{2}\sigma}\right)
\end{aligned}$$

Performance of likelihood-ratio decoding in WGN

- False alarm probability is

$$\begin{aligned} P_{fa} =& P(D_1|H_0)P(H_0) \\ =& P(H_0)\int_T^{\infty} w(r|H_0) \\ =& P(H_0)(F(\infty) - F(T)) \\ =& \frac{1}{4}\left(1 - erf\left(\frac{T-0}{\sqrt{2}\sigma}\right)\right) \\ =& Q\left(\frac{T}{\sqrt{2}\sigma}\right) \end{aligned}$$

- Therefore $\frac{T}{\sqrt{2}\sigma} = Q^{-1}\left(P_{fa}\right)$
- Replacing in P_{hit} yields

$$P_{hit} = Q\left(\underbrace{Q^{-1}\left(P_{fa}\right)}_{constant} - \frac{A}{\sqrt{2}\sigma}\right)$$

Signal-to-noise ratio

- **Signal-to-noise ratio (SNR)** $= \frac{\text{power of original signal}}{\text{power of noise}}$
- Average power of a signal = average squared value = $\overline{X^2}$
  - Original signal power is $\frac{A^2}{2}$
  - Noise power is $\overline{X^2} = \sigma^2$ (when noise mean value $\mu = 0$)
- In our case, SNR $= \frac{A^2}{2\sigma^2}$

$$P_{hit} = Q\left(\underbrace{Q^{-1}\left(P_{fa}\right)}_{constant} - \sqrt{SNR}\right)$$

- For a fixed P_{fa}, P_{hit} increases with SNR
  - Q is a monotonic decreasing function

Performance depends on SNR

- Receiver performance increases with SNR increase
  - high SNR: good performance
  - poor SNR: bad perfomance

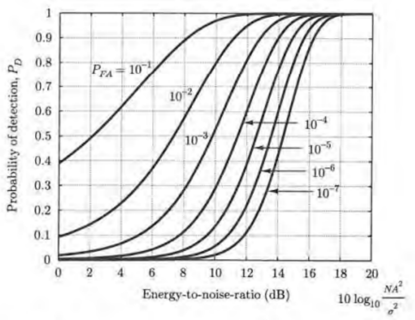

Figure 4: Detection performance depends on SNR

[source: Fundamentals of Statistical Signal Processing, Steven Kay]

Decision between hypotheses

- Statistical decision is not useful merely for detecting signals
- We are in fact deciding between two different probability distributions
  - regardless of what the two distributions mean
- For detection of constant signals, we choose between two distributions with **different average value**, generally
  - one distribution has average value 0, the other one A
- But we can choose between distributions that differ in other parameters
  - average value, or
  - variance, or
  - shape, etc

Decision between hypotheses

- Example: We have a sample with value $r = 2.5$. It can come from a distribution $\mathcal{N}(0, \sigma^2 = 1)$ (hypothesis H_0) or from $\mathcal{N}(0, \sigma^2 = 2)$ (hypothesis H_1). Which hypothesis do we think is true?
  - It is the variance that differs, not the average value
- We can use the exact same criteria as before
  - Draw the two distributions
  - Compute the likelihoods $w(r|H_0)$ and $w(r|H_1)$ for r
  - Decide based on likelihood ratio using some criterion

II.3 Detection of constant signals with multiple samples

Multiple samples from a constant signal

- Suppose we have multiple samples, not just 1
- The samples are arranged in a **sample vector**

$$\mathbf{r} = [r_1, r_2, ...r_N]$$

- In each hypotheses, the signal is a **random process**
  - H_0: random process with average value 0
  - H_1: random process with average value A
- Assuming the noise is stationary and ergodic, the signal random process is stationary and ergodic (signal = constant + noise)
- The values of **r** are described by the **distribution of order** N of the random processes, $w_N(\mathbf{r}) = w_N(r_1, r_2, ...r_N)$
- Assuming the noise is white noise, the sample times don't matter

Likelihood of vector samples

- We can apply **the same criteria** based on likelihood ratio as for 1 sample

$$\frac{w_N(\mathbf{r}|H_0)}{w_N(\mathbf{r}|H_1)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- Notes
  - $\mathbf{r}$ is a vector; we consider the likelihood of all the samples
  - the hypotheses H_0 and H_1 are the same as for 1 sample
  - $w_N(\mathbf{r}|H_0) =$ likelihood of the whole vector $\mathbf{r}$ being obtained in hypothesis H_0
  - $w_N(\mathbf{r}|H_1) =$ likelihood of the whole vector $\mathbf{r}$ being obtained in hypothesis H_1
  - the value of K is given by the actual decision criterion used
- Interpretation: we choose the hypothesis that is most likely to have produced the observed data
  - the same, but now the data = multiple samples

Separation

- Assuming the noise is white noise, the samples r_i are **multiple independent realizations of the same distribution**
- In that case the joint distributions $w_N(\mathbf{r}|H_j)$ can be decomposed as a product

$$w_N(\mathbf{r}|H_j) = w(r_1|H_j) \cdot w(r_2|H_j) \cdot ... \cdot w(r_N|H_j)$$

- The $w(r_i|H_j)$ are just the likelihoods of each individual sample
  - e.g. the likelihood of obtaining $[5.1, 4.7, 4.9]$ = likelihood of obtaining 5.1 $\times$ likelihood of getting 4.7 $\times$ likelihood of getting 4.9

Separation

- Then all likelihood ratio criteria can be written as

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{w(r_1|H_1)}{w(r_1|H_0)} \cdot \frac{w(r_2|H_1)}{w(r_2|H_0)} \dots \frac{w(r_N|H_1)}{w(r_N|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- The likelihood ratio of a vector of samples = product of likelihood ratio for each sample

Particular case: AWGN

- AWGN = "Additive White Gaussian Noise"
- In hypothesis H_1: $w(r_i|H_1) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r_i-A)^2}{2\sigma^2}}$
- In hypothesis H_0: $w(r_i|H_1) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{r_i^2}{2\sigma^2}}$
- Likelihood ratio for vector $\mathbf{r}$

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{e^{-\frac{\sum (r_i-A)^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}}$$

- We can interpret this likelihood ratio in three ways

Interpretation 1: average value of samples

- Interpretation 1: average value of samples

$$
\begin{aligned}
\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} &= \frac{e^{-\frac{\sum (r_i - A)^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}} \\
&= e^{-\frac{\sum (r_i - A)^2 - \sum (r_i)^2}{2\sigma^2}} \\
&= e^{-\frac{\sum (r_i^2 - 2 r_i A + A^2) - \sum (r_i)^2}{2\sigma^2}} \\
&= e^{-\frac{\sum (-2 r_i A + A^2)}{2\sigma^2}} \\
&= e^{-\frac{-2A \sum (r_i) + N A^2}{2\sigma^2}} \\
&= e^{-\frac{-2A \frac{\sum (r_i)}{N} + A^2}{2 \frac{\sigma^2}{N}}}
\end{aligned}
$$

Average value of N gaussian random variables

- Let U_r = average value of the samples r_i

$$U_r = \frac{1}{N} \sum r_i$$

- What distribution does it have?
- Consider the sum $S_r = \sum r_i$ of the N samples r_i
  - From chapter 1: the sum of normal r.v. $\mathcal{N}(\mu, \sigma^2)$ has:
  - normal distribution $\mathcal{N}(\mu_S, \sigma_S^2)$ with
  - average value: $\mu_S = N \cdot \mu$
  - variance: $\sigma_S^2 = N \cdot \sigma^2$
- Then $U_r = \frac{1}{N} S_r$, and from the properties of average values we have
  - U_r has normal distribution with:
  - average value $= \frac{1}{N} \mu_S = \frac{1}{N} N \mu = \mu$
  - variance $= \left(\frac{1}{N}\right)^2 \sigma_S^2 = \left(\frac{1}{N}\right)^2 N \sigma_S^2 = \frac{1}{N} \sigma^2$

Average value of N gaussian random variables

- The mean value of N realizations of a normal distribution has a normal distribution with
  - same average value
  - variance N times smaller
- If N gets very large, the mean value is a very good **estimator** of the distribution's average value
  - its distribution gets very narrow around the average value

Interpretation 1: average value of samples

$$\begin{aligned}
\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} &= e^{-\frac{-2AU_r+A^2}{2\frac{\sigma^2}{N}}} \\
&= \frac{e^{-\frac{U_r^2-2AU_r+A^2}{2\frac{\sigma^2}{N}}}}{e^{-\frac{U_r^2}{2\frac{\sigma^2}{N}}}} \\
&= \frac{e^{-\frac{(U_r-A)^2}{2\frac{\sigma^2}{N}}}}{e^{-\frac{U_r^2}{2\frac{\sigma^2}{N}}}} \\
&= \frac{w(U_r|H_1)}{w(U_r|H_0)}
\end{aligned}$$

- The likelihood ratio of N gaussian samples = the likelihood ratio of **the mean of the samples**

Interpretation 1: average value of samples

- The likelihood ratio of N gaussian samples = the likelihood ratio of **the mean of the samples**
  - the mean has smaller variance $\frac{1}{N}\sigma^2$, so is more accurate
  - it is like the noise distribution gets N times narrower (due to averaging)
- Detection of constant signals with N samples is the same as detection with 1 sample, but:
  - use the average value of the samples r_i
  - its distributions are N times narrower (variance is N times smaller)
- As N increases, the probability of errors decrease => better performance

Exercise

Exercise:

- A signal can have two values, 0 (hypothesis H_0) or 6 (hypothesis H_1). The signal is affected by AWGN $\mathcal{N}(0, \sigma^2 = 1)$. The receiver takes 5 samples with values $\{1.1, 4.4, 3.7, 4.1, 3.8\}$.
    1. What is decision according to Maximum Likelihood criterion?
    2. What is decision according to minimum probability of error criterion, assuming $P(H_0) = 2/3$ and $P(H_1) = 1/3$?

Interpretation 2: geometrical

- Useful mainly for Maximum Likelihood criterion
- Likelihood ratio for vector **r**

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{e^{-\frac{\sum (r_i - A)^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- For Maximum Likelihood we compare to 1

$$\frac{e^{-\frac{\sum (r_i - A)^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

$$e^{-\frac{\sum (r_i - A)^2}{2\sigma^2} + \frac{\sum (r_i)^2}{2\sigma^2}} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

$$-\sum (r_i - A)^2 + \sum (r_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} 0$$

$$\sum (r_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} \sum (r_i - A)^2$$

Interpretation 2: geometrical

- $\sqrt{\sum(r_i)^2}$ is the geometrical (Euclidian) distance between point $\mathbf{r} = [r_1, r_2, ...r_N]$ and point $\mathbf{0} = [0, 0, ...0]$
- $\sqrt{\sum(r_i - A)^2}$ is the geometrical (Euclidian) distance between point $\mathbf{r} = [r_1, r_2, ...r_N]$ and point $\mathbf{A} = [A, A, ...A]$
- ML decision chooses **the closest signal vector (point)** to the received vector (point), in a N-dimensional space
  - it is known as "minimum distance receiver"
  - same interpretation as in the 1-D case
- Question: what is the geometrical interpretation for the other criteria?

Exercise

Exercise:

- A signal can have two values, 0 (hypothesis H_0) or 6 (hypothesis H_1). The signal is affected by AWGN $\mathcal{N}(0, \sigma^2 = 1)$. The receiver takes 2 samples with values $\{1.1, 4.4\}$.
    1. What is decision according to Maximum Likelihood criterion? Use the geometrical interpretation.

Interpretation 3: cross-correlation

- Likelihood ratio for vector $\mathbf{r}$

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{e^{-\frac{\sum (r_i - A)^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

$$e^{-\frac{\sum (r_i - A)^2}{2\sigma^2} + \frac{\sum (r_i)^2}{2\sigma^2}} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

$$-\sum (r_i - A)^2 + \sum (r_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \ln K$$

$$2 \sum r_i A - N A^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \ln K$$

$$\frac{1}{N} \sum r_i A \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{\frac{A^2}{2} + \frac{1}{N} \sigma^2 \ln K}_{L = const}$$

Interpretation 3: cross-correlation

- The **cross-correlation** (sometimes just "the correlation") of two signals x and y is

$$< x, y >= \frac{1}{N} \sum x[n]y[n]$$

- It is the value of the correlation function in 0

$$< x, y >= R_{xy}[0] = \overline{x[n]y[n+0]}$$

- For continuous signals

$$< x, y >= \frac{1}{T} \int_{T/2}^{T/2} x(t)y(t)dt$$

- $\frac{1}{N} \sum r_i A =< \mathbf{r}, \mathbf{A} >$ is the cross-correlation of the received samples $\mathbf{r} = [r_1, r_2, ...r_N]$ with the **target** samples $\mathbf{A} = [A, A, ...A]$

Interpretation 3: cross-correlation

- If the cross-correlation of the received samples with the target samples $\mathbf{A} = [A, A, ...A]$ is greater than a certain threshold L, we decide that signal is detected.
  - otherwise, the signal is rejected
- This is **similar to signal detection based on 1 sample**, with the sample value being $< \mathbf{r}, \mathbf{A} >$

Cross-correlation as a measure of similarity

- Cross-correlation in signal processing measures **similarity** of two signals
- Interpretation: we check if the received samples look similar enough to the constant signal A
  - If yes (high cross-correlation) $=>$ signal detected
  - If no (low cross-correlation) $=>$ no detection

Generalization: two non-zero values

- Generalization: two non-zero signal values, B and A
  - still with Gaussian noise
- Interpretation 1: average value of samples
  - use mean of samples, the two distributions are centered on B and A
- Interpretation 2: geometric (Maximum Likelihood)
  - choose minimum Euclidean distance from $\mathbf{r} = [r_1, r_2, ...r_N]$ to points $\mathbf{B} = [B, B, ...]$ and $\mathbf{A} = [A, A, ...]$
- Interpretation 3: cross-correlation
  - compute $< \mathbf{r}, \mathbf{B} >$ and $< \mathbf{r}, \mathbf{A} >$, cross-correlation of $\mathbf{r}$ with $\mathbf{B} = [B, B, ...]$ and with $\mathbf{A} = [A, A, ...]$.
  - see next slide

Detection between two non-zero values with cross-correlation

$$e^{-\frac{\sum (r_i - A)^2}{2\sigma^2} + \frac{\sum (r_i - B)^2}{2\sigma^2}} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

$$-\sum (r_i - A)^2 + \sum (r_i - B)^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \ln K$$

$$2\sum r_i A - NA^2 - 2\sum r_i B + NB^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \ln K$$

$$\frac{1}{N}\sum r_i A - \frac{A^2}{2} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{1}{N}\sum r_i B - \frac{B^2}{2} + \frac{1}{N}\sigma^2 \ln K$$

Detection between two non-zero values with cross-correlation

- For Maximum Likelihood ($K = 1$):

$$< \mathbf{r}, \mathbf{A} > - \frac{< \mathbf{A}, \mathbf{A} >}{2} \underset{H_0}{\overset{H_1}{\gtrless}} < \mathbf{r}, \mathbf{B} > - \frac{< \mathbf{B}, \mathbf{B} >}{2}$$

- If the two values are opposite, $B = -A$, choose the most similar to $\mathbf{r}$:
  - cross-correlation measures similarity

$$< \mathbf{r}, \mathbf{A} > \underset{H_0}{\overset{H_1}{\gtrless}} < \mathbf{r}, -\mathbf{A} >$$

- For other criteria: with an extra offset factor $\frac{1}{N}\sigma^2 \ln K$

Exercise

Exercise:

- A signal can have two values, -4 (hypothesis H_0) or 5 (hypothesis H_1). The signal is affected by AWGN $\mathcal{N}(0, \sigma^2 = 1)$. The receiver takes 3 samples with values $\{1.1, 4.4, 2.2\}$.
  1. What is decision according to Maximum Likelihood criterion? Use all three interpretations.

II.4 Detection of general signals with multiple samples

Multiple samples from a general (non-constant) signal

- We want to detect a **general (non-constant)** signal $s(t)$
- The N samples are taken at times $\mathbf{t} = [t_1, t_2, ...t_N]$ and are arranged in a **sample vector**

$$\mathbf{r} = [r_1, r_2, ...r_N]$$

- What changes compared to constant signals?

Hypotheses

- In each hypothesis, the signal is a **random process**
  - H_0: random process with average value 0
  - H_1: random process with average value $s(t)$
- The sample r_i, at time t_i, is:
  - $0 +$ noise, in hypothesis H_0
  - $s(t_i) +$ noise, in hypothesis H_1
- The whole sample vector $\mathbf{r}$ is
  - $0 +$ noise, in hypothesis H_0
  - $s(t) +$ noise, in hypothesis H_1, for t being all the sample times t_i
- The distribution of the whole vector $\mathbf{r}$ is described by a function $w_N(\mathbf{r})$

Likelihood of vector samples

- We can apply **the same criteria** based on likelihood ratio as for constant signals:

$$\frac{w_N(\mathbf{r}|H_0)}{w_N(\mathbf{r}|H_1)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- The difference is that the "true" underlying signals are now
  - [0, 0, . . . 0] in hypothesis H_0
  - $[s(t_1), s(t_2), ...s(t_N)]$ in hypothesis H_1

Separation

- The joint distribution $w_N(\mathbf{r}|H_j)$ can be decomposed as a product

$$w_N(\mathbf{r}|H_j) = w(r_1|H_j) \cdot w(r_2|H_j) \cdot ... \cdot w(r_N|H_j)$$

- Then all likelihood ratio criteria can be written as

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{w(r_1|H_1)}{w(r_1|H_0)} \cdot \frac{w(r_2|H_1)}{w(r_2|H_0)} ... \frac{w(r_N|H_1)}{w(r_N|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- The likelihood ratio of a sample r_i is computed considering the two possible values of the underlying signal, 0 and $s(t_i)$
  - for constant signals, the two values were 0 and A all the time
  - now they are 0 and $s(t_i)$, depending on the sample times t_i
  - the sample times t_i should be chosen such as to maximize the performance of detection

Particular case: AWGN

- AWGN = "Additive White Gaussian Noise"
- In hypothesis H_1: $w(r_i|H_1) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r_i - s(t_i))^2}{2\sigma^2}}$
- In hypothesis H_0: $w(r_i|H_1) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{r_i^2}{2\sigma^2}}$
- Likelihood ratio for vector $\mathbf{r}$

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{e^{-\frac{\sum (r_i - s(t_i))^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}}$$

- We can interpret this likelihood ratio in two ways

Interpretation 1: average value of samples

- Interpretation 1: average value of samples
- Cannot be used anymore, since the values $s(t_i)$ are not the same

Interpretation 2: geometrical

- Useful mainly for Maximum Likelihood criterion
- Likelihood ratio for vector $\mathbf{r}$

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{e^{-\frac{\sum (r_i - s(t_i))^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

- For Maximum Likelihood we compare to 1

$$\frac{e^{-\frac{\sum (r_i - s(t_i))^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

$$e^{-\frac{\sum (r_i - s(t_i))^2}{2\sigma^2} + \frac{\sum (r_i)^2}{2\sigma^2}} \underset{H_0}{\overset{H_1}{\gtrless}} 1$$

$$-\sum (r_i - s(t_i))^2 + \sum (r_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} 0$$

$$\sum (r_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} \sum (r_i - s(t_i))^2$$

Interpretation 2: geometrical

- $\sqrt{\sum(r_i)^2}$ is the geometrical (Euclidian) distance between point $\mathbf{r} = [r_1, r_2, ...r_N]$ and point $\mathbf{0} = [0, 0, ...0]$
- $\sqrt{\sum(r_i - s(t_i))^2}$ is the geometrical (Euclidian) distance between point $\mathbf{r} = [r_1, r_2, ...r_N]$ and point $\mathbf{s(t)} = [s(t_1), s(t_2), ...s(t_N)]$
- ML decision chooses **the closest signal vector (point)** to the received vector (point), in a N-dimensional space
  - it is known as "minimum distance receiver"
  - same interpretation as in the 1-D case
- Question: what is the geometrical interpretation for the other criteria?

Exercise

Exercise:

- Consider detecting a signal $s(t) = 3\sin(2\pi f_1 t)$ that can be present (hypothesis H_1) or not (hypothesis H_0). The signal is affected by AWGN $\mathcal{N}(0, \sigma^2 = 1)$. The receiver takes 2 samples.
  1. What are the best sample times t_1 and t_2 to maximize detection performance?
  2. The receiver takes 2 samples with values $\{1.1, 4.4\}$, at sample times $t_1 = \frac{0.125}{f_1}$ and $t_2 = \frac{0.625}{f_1}$. What is decision according to Maximum Likelihood criterion? Use the geometrical interpretation.
  3. What if the receiver takes an extra third sample at time $t_3 = \frac{0.5}{f_1}$. Will the detection be improved?

Interpretation 3: cross-correlation

- Likelihood ratio for vector $\mathbf{r}$

$$\frac{w_N(\mathbf{r}|H_1)}{w_N(\mathbf{r}|H_0)} = \frac{e^{-\frac{\sum (r_i - s(t_i))^2}{2\sigma^2}}}{e^{-\frac{\sum (r_i)^2}{2\sigma^2}}} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

$$e^{-\frac{\sum (r_i - s(t_i))^2}{2\sigma^2} + \frac{\sum (r_i)^2}{2\sigma^2}} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

$$-\sum (r_i - s(t_i))^2 + \sum (r_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \ln K$$

$$2 \sum r_i s(t_i) - \sum s(t_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \ln K$$

$$\frac{1}{N} \sum r_i s(t_i) \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{\frac{1}{2} \frac{\sum s(t_i)^2}{N} + \frac{1}{N} \sigma^2 \ln K}_{L = const}$$

Interpretation 3: cross-correlation

- $\frac{1}{N}\sum r_i s(t_i)$ is the cross-correlation of the received samples $\mathbf{r} = [r_1, r_2, ...r_N]$ with the **target** samples $\mathbf{s(t_i)} = [s(t_1), s(t_2), ...s(t_N)]$
- If the cross-correlation of the received samples with the target samples $\mathbf{s(t_i)}$ is greater than a certain threshold L, we decide that signal is detected.
  - otherwise, the signal is rejected
  - cross-correlation is a measure of similarity

Generalization: two non-zero signals

- Generalization: decide between **two different signals** $s_0(t)$ and $s_1(t)$
  - still with Gaussian noise
- Interpretation 2: geometric
  - choose minimum Euclidean distance from $\mathbf{r} = [r_1, r_2, ...r_N]$ to points $\mathbf{s_0(t)} = [s_0(t_1), s_0(t_2), ...]$ and $\mathbf{s_1(t)} = [s_1(t_1), s_1(t_2), ...]$
- Interpretation 3: cross-correlation
  - compute cross-correlation of $\mathbf{r}$ with $\mathbf{s_0(t)} = [s_0(t_1), s_0(t_2), ...]$ and with $\mathbf{s_1(t)} = [s_1(t_1), s_1(t_2), ...]$, $< \mathbf{r}, \mathbf{s_0} >$ and $< \mathbf{r}, \mathbf{s_1} >$.
  - see next slide

Detection between two non-zero signals with cross-correlation

$$e^{-\frac{\sum (r_i - s_1(t_i))^2}{2\sigma^2} + \frac{\sum (r_i - s_0(t_i))^2}{2\sigma^2}} \underset{H_0}{\overset{H_1}{\gtrless}} K$$

$$-\sum (r_i - s_1(t_i))^2 + \sum (r_i - s_0(t_i))^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \ln K$$

$$2\sum r_i s_1(t_i) - \sum s_1(t_i)^2 - 2\sum r_i s_0(t_i) + \sum s_0(t_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma^2 \ln K$$

$$\frac{1}{N}\sum r_i s_1(t_i) - \sum s_1(t_i)^2 \underset{H_0}{\overset{H_1}{\gtrless}} \frac{1}{N}\sum r_i s_0(t_i) - \sum s_0(t_i)^2 + \frac{1}{N}\sigma^2 \ln K$$

Detection between two non-zero signals with cross-correlation

- For Maximum Likelihood ($K = 1$):

$$< \mathbf{r}, \mathbf{s_1} > - \frac{< \mathbf{s_1}, \mathbf{s_1} >}{2} \underset{H_0}{\overset{H_1}{\gtrless}} < \mathbf{r}, \mathbf{s_0} > - \frac{< \mathbf{s_0}, \mathbf{s_0} >}{2}$$

- If the two signals have the same energy: $\sum s_1(t_i)^2 = \sum s_0(t_i)^2$, then $< \mathbf{s_1}, \mathbf{s_1} > = < \mathbf{s_0}, \mathbf{s_0} >$, so we choose **the signal most similar to r**:
  - cross-correlation measures similarity

$$< \mathbf{r}, \mathbf{s_1} > \underset{H_0}{\overset{H_1}{\gtrless}} < \mathbf{r}, \mathbf{s_0} >$$

- Examples:
  - BPSK modulation: $s_1 = A\cos(2\pi f t)$, $s_0 = -A\cos(2\pi f t)$
  - 4-PSK modulation: $s_{n=0,1,2,3} = A\cos(2\pi f t + n\frac{\pi}{4})$

IMAGE

- PUT IMAGE HERE

Matched filters

- How to compute the cross-correlation of two signals $r[n]$ and $s[n]$ of length N?

$$< r, s >= \frac{1}{N} \sum r_i s(t_i)$$

- The **convolution** of $r[n]$ and $s[n]$ is given by

$$y[n] = \sum_k r[k] s[n-k]$$

- Let $s'[n]$ be the signal $s[n]$ **flipped / mirrored** ("oglindit")
  - still starting from time 0 onwards, we want causality

$$s'[n] = s[N-n]$$

- The convolution of $r[n]$ with $s'[n]$ is

$$y'[n] = \sum_k r[k] s'[n-k] = \sum_k r[k] s[N-n+k]$$

- The convolution sampled at the end of the signal, $y[N]$ $(n = N)$, is the cross-correlation
  - up to a scaling constant $\frac{1}{N}$

Matched filters

- To detect a signal $s[n]$ we can use a **filter with impulse response = mirrored version of** $s[n]$, and take the final sample of the output
  - it is identical to computing the cross-correlation
- **Matched filter** = a filter designed to have the impulse response the flipped version of a signal we search for
  - the filter is *matched* to the signal we want to detect
  - rom. "filtru adaptat"

Matched filters

IMAGE HERE

II.5 Detection of general signals with continuous observations

Continuous observation of a general signal

- Continuous observation = we don't take samples anymore, we use **all the continuous signal**
  - like taking N samples but with $N \to \infty$
- Received signal is $r(t)$
- Target signal is $s(t)$
- Assume Gaussian noise only
- How to detect?

Detection

- Extend the previous case of N samples to the case a full continuous signal
- Interpretation 1: average value of samples
  - Cannot be used anymore, since the values $s(t_i)$ are not the same

Interpretation 2: geometrical

- Interpretation 2: geometrical
- Each signal $r(t)$, $s(t)$ or 0 is a data point in an infinite-dimensional Euclidean space
- Distance between two signals is

$$d(r,s) = \sqrt{\int (r(t) - s(t))^2 \, dt}$$

- Similar with the N dimensional case, but with integral instead of sum
- Maximum Likelihood criterion:
    - compute distance $d(r,s)$ from $r(t)$ to $s(t)$
    - compute distance $d(r,0)$ from $r(t)$ to 0
    - choose the minimum

Interpretation 3: cross-correlation

- The cross correlation of a continuous signal $r(t)$ with a target signal $s(t)$ of length T

$$< \mathbf{r}, \mathbf{s} >= \frac{1}{T}\int_0^T r(t) \cdot s(t) dt$$

- If the cross-correlation of the received signal with the true signal $\mathbf{s(t_i)}$ is greater than a certain threshold L, we decide that signal is detected.
  - otherwise, the signal is rejected
  - cross-correlation is a measure of similarity

Generalizations

- Detection **between two signals** $s_0(t)$ and $s_1(t)$
  - still with Gaussian noise
- Interpretation 2: geometric
  - choose minimum Euclidean distance from point $\mathbf{r(t)}$ to points $\mathbf{s_0(t)}$ and $\mathbf{s_1(t)}$
    - using the specified distance formula
- Interpretation 3: cross-correlation
  - compute cross-correlation of $\mathbf{r(t)}$ with $\mathbf{s_0(t)}$ and with $\mathbf{s_1(t)}$.

Detection between two non-zero signals with cross-correlation

- For Maximum Likelihood ($K = 1$):

$$< \mathbf{r}, \mathbf{s_1} > - \frac{< \mathbf{s_1}, \mathbf{s_1} >}{2} \underset{H_0}{\overset{H_1}{\gtrless}} < \mathbf{r}, \mathbf{s_0} > - \frac{< \mathbf{s_0}, \mathbf{s_0} >}{2}$$

- If the two signals have the same energy: $\int s_1(t)^2 dt = \int s_0(t)^2 dt$, then $< \mathbf{s_1}, \mathbf{s_1} > = < \mathbf{s_0}, \mathbf{s_0} >$, so we choose **the signal most similar to r**:
  - cross-correlation measures similarity

$$< \mathbf{r}, \mathbf{s_1} > \underset{H_0}{\overset{H_1}{\gtrless}} < \mathbf{r}, \mathbf{s_0} >$$

- Examples:
  - BPSK modulation: $s_1 = A\cos(2\pi f t)$, $s_0 = -A\cos(2\pi f t)$
  - 4-PSK modulation: $s_{n=0,1,2,3} = A\cos(2\pi f t + n\frac{\pi}{4})$

Matched filters

- Cross-correlation of signals can be computed with **matched filters**
- **Matched filter** = a filter designed to have the impulse response the flipped version of a signal we search for
  - the filter is *matched* to the signal we want to detect
  - rom. "filtru adaptat"
  - filter is continuous, continuous impulse response
- To detect a signal $s(t)$ we use a matched filter and take the sample of the output at the final moment of the input signal
  - it is identical with computing cross-correlation

Matched filters

IMAGE HERE