

DSP Evaluation Project

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Monostatic Pulse Radar

- Mono-static: the transmitter and receiver are collocated
- Pulse: short and powerful pulses followed by the silent period during which the echo signals are received
- Metrics for performance of non-coherent detection
 - Probability of False Alarm
 - Probability of Missed Detection = $1 - \text{Probability of Detection}$

Received Power Computation

- From Friis transmission equation,

$$P_r = \frac{P_t G_t}{4\pi r^2} \sigma \frac{1}{4\pi r^2} A_{\text{eff}}$$

where

- P_t = transmitter's input power (watts)
- G_t = **gain** of the radar transmit antenna (dimensionless)
- r = distance from the radar to the target (meters)
- σ = radar cross-section of the target (meters squared)
- A_{eff} = effective area of the radar receiving antenna (meters squared)
- P_r = power received back from the target by the radar (watts)

- Assuming lossless isotropic Rx antenna,

$$A_{\text{eff}} = \frac{\lambda^2}{4\pi}$$

Noise Power Consideration

- Thermal noise (in dBm) = $-174 + 10 \cdot \log_{10}(F_s)$
 - F_s is the sampling frequency
 - Pulse BW is selected as F_s , which is Nyquist rate.
 - Pulse BW = $1/\text{pulse width} = c/(2 \cdot \text{range_resolution})$
 - c is a light speed
 - required range resolution is given as 50m

Readme for Matlab file

- Run “radar.m”
- The following parameters are hard-coded
 - $F_c = 100\text{MHz}$
 - Tx Power = 5kW
 - 10 repetitions of pulses
 - detection threshold = $0.2e-13$
- It tries a single pulse 100000 times for PFA and PD computation

```
>> radar  
At SNR = 4.82 (dB)  
Probability of Detection = 0.98.....PASSED  
Probability of False Alarm = 0.00.....PASSED
```

Gaussian Noise Generator

- Basically, it is an inverse CDF-based generator
 - Pick a random number between $[0,1)$
 - Apply ICDF to generate the corresponding noise sample
 - When applying ICDF, use 2nd-order polynomial approximation

Implementation Details

- Since ICDF is symmetric, only the positive part needs to be generated. One sign bit determines if we need to negate the result at the end
- Segment generation
 - A total of 128 segments(=7bits) are generated (32 from LZD and 4 from OFFSET)
 - Leading zero detector is for making $1/2^5$ probability segment
 - Further refine each segment to 4 equal pieces
- Generated segments and polynomial coefficients are stored in the lookup tables

Readme for Matlab file

- Run “[grn_val, test_vec] = GNG”
- Gaussian Noise Sample with zero-mean and unit-variance will be generated

```
>> [grn_val, test_vec] = GNG

grn_val =

    1.5341

test_vec =
|
struct with fields:

    URNG_OUT: [1×64 double]
        SIGN: 0
        OFFSET: [1 0]
    LZD_INPUT: [1×61 double]
        SEGMENT: [1 0 1 1 0 0 0]
        MASK_IN: [0 1 1 1 1 0 0 1 1 0 1 1 1 0 0]
        MASK_OUT: [0 1 1 1 1 0 0 1 1 0 1 1 1 0 0]
        MULT_IN: [0 0 1 1 1 0 1 1 0 0 1 1 1 1 0]
        COEF0: [0 0 1 0 1 1 1 1 0 1 0 0 0 1 0 0 0 1 1 0 0]
        COEF1: [0 0 0 0 0 1 1 1 0 0 0 0 0 0 1 0 0 0]
        COEF2: [0 1 1 0 1 0 0 1 1 1 0 0 0 0 0 0 0]
        INTERM: [0 0 0 0 1 1 1 0 0 0 0 0 0 1 0 0 0]
        POLYOUT: [0 0 0 1 1 0 0 0 1 0 0 0 1 1 0 0]
        GRNOUT: [0 0 0 1 1 0 0 0 1 0 0 0 1 1 0 0]
```


Kalman Filter Basics

- It consists of three stages
 - Projection
 - Kalman Gain Computation
 - New estimation and update covariance matrix

Description	Equation
Kalman Gain	$K_k = P'_k H^T (H P'_k H^T + R)^{-1}$
Update Estimate	$\hat{x}_k = \hat{x}'_k + K_k (z_k - H \hat{x}'_k)$
Update Covariance	$P_k = (I - K_k H) P'_k$
Project into $k + 1$	$\begin{aligned}\hat{x}'_{k+1} &= \Phi \hat{x}_k \\ P_{k+1} &= \Phi P_k \Phi^T + Q\end{aligned}$

Extended KF

- Extended KF is KF's extension to a non-linear system by taking the first order linear approximation to get matrix Φ or H .

$$\tilde{\mathbf{x}} = \mathbf{f}(\hat{\mathbf{x}}, \mathbf{u}) \quad \tilde{\mathbf{y}} = \mathbf{h}(\tilde{\mathbf{x}}, \mathbf{u})$$

$$\text{I) } \mathbf{F} = \left. \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \right|_{\mathbf{x}=\hat{\mathbf{x}}} \quad \mathbf{H} = \left. \frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}} \right|_{\mathbf{x}=\hat{\mathbf{x}}}$$

$$\text{II) } \tilde{\mathbf{P}} = \mathbf{F}\hat{\mathbf{P}}\mathbf{F}^T + \mathbf{Q}$$

$$\text{III) } \mathbf{K} = \tilde{\mathbf{P}}\mathbf{H}^T [\mathbf{H}\tilde{\mathbf{P}}\mathbf{H}^T + \mathbf{R}]^{-1}$$

$$\text{IV) } \hat{\mathbf{x}} = \tilde{\mathbf{x}} + \mathbf{K}(\mathbf{y} - \tilde{\mathbf{y}})$$

$$\text{V) } \hat{\mathbf{P}} = \tilde{\mathbf{P}} - \mathbf{K}\mathbf{H}\tilde{\mathbf{P}}$$

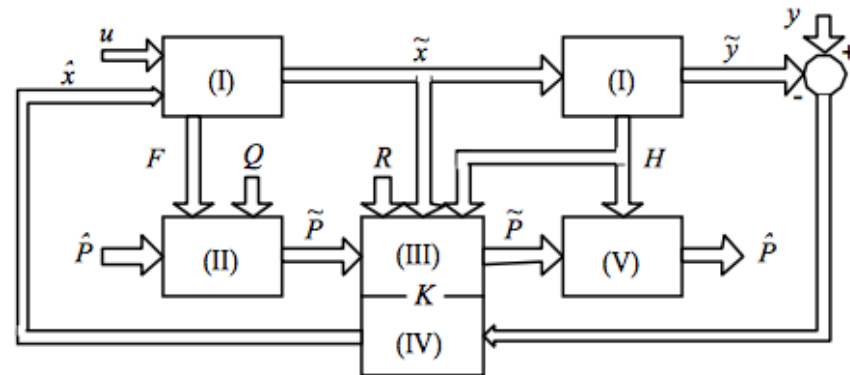


Fig. 1. EKF recursive computational scheme.

Rotor with Kalman Filter Representation

- Substituting the following variables to the previous equations yield the results on the next slide

$$\mathbf{x}_k = [\cos \theta_k \quad \sin \theta_k \quad \omega_k]^T \quad \mathbf{y}_k = [\cos \theta_k \quad \sin \theta_k]^T \quad \mathbf{u}_k = [0 \quad 0]^T \quad (5)$$

$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k, \mathbf{k}) = \begin{pmatrix} x_1 \cdot \cos(\omega_b T_{sc} \cdot x_3) - x_2 \cdot \sin(\omega_b T_{sc} \cdot x_3) \\ x_1 \cdot \sin(\omega_b T_{sc} \cdot x_3) + x_2 \cdot \cos(\omega_b T_{sc} \cdot x_3) \\ x_3 \end{pmatrix} \quad \mathbf{y}_k = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \cdot \mathbf{x}_k \quad (6)$$

$$\mathbf{Q} = q\mathbf{I}_{3 \times 3} \quad \mathbf{R} = r\mathbf{I}_{2 \times 2} \quad (7)$$

Readme for Matlab file

- Run “rotor”

