


Radar Signal Detection


Radar systems (Radarové systémy)

Radar signal processing

- Primary processing

- Processing of signal within one antenna revolution – one PRI or several adjacent PRIs
 - Pulse compression
 - Doppler filtration
 - Target detection 

- Secondary processing

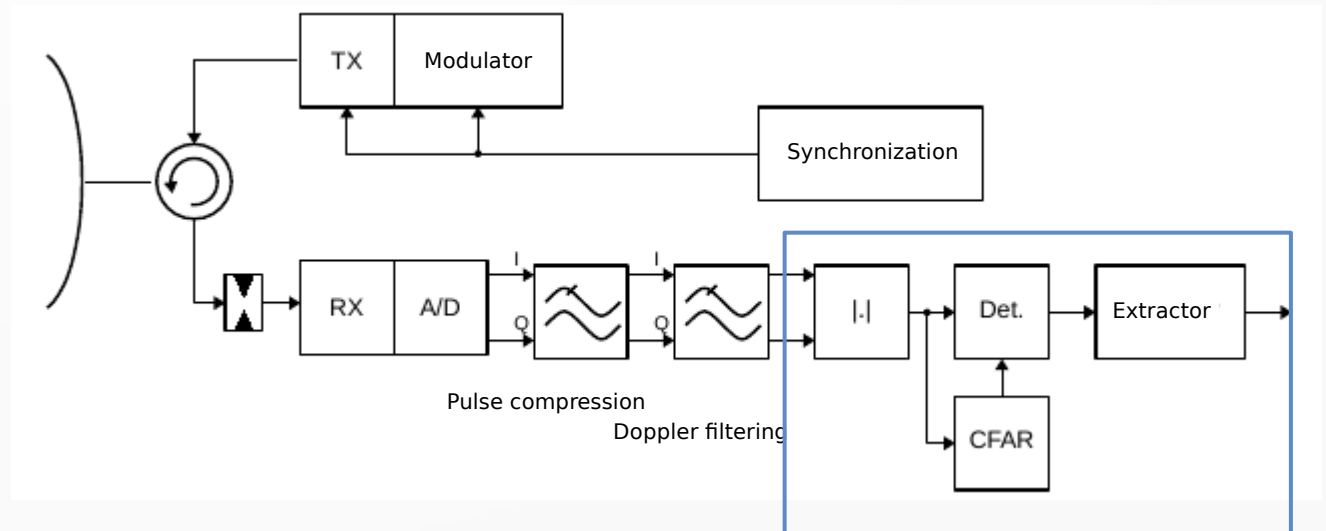
- Processing of several revolutions
 - Target tracking 
 - Clutter mapping for adaptive processing

- Tertiary processing

- Data fusion – signal processing from several radar sites

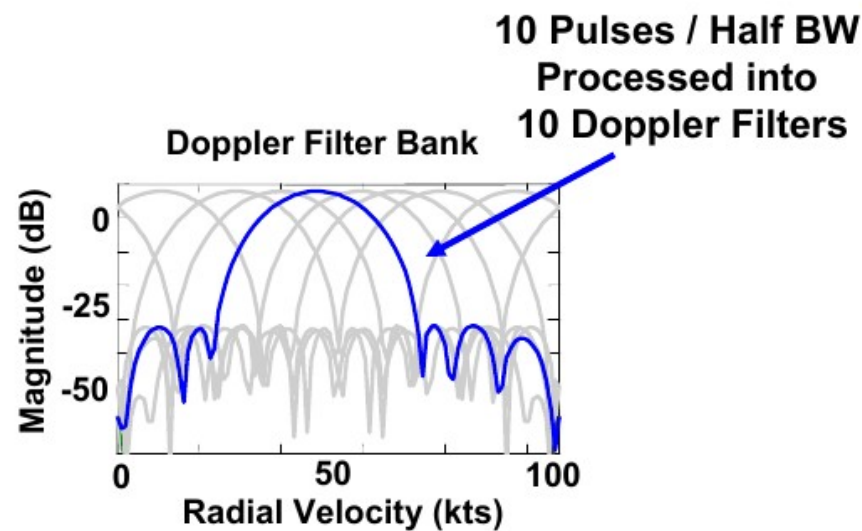
Radar signal processing

- Primary processing
 - Signal detection
 - Extraction



Range-Azimuth-Doppler Cells to Be Thresholded

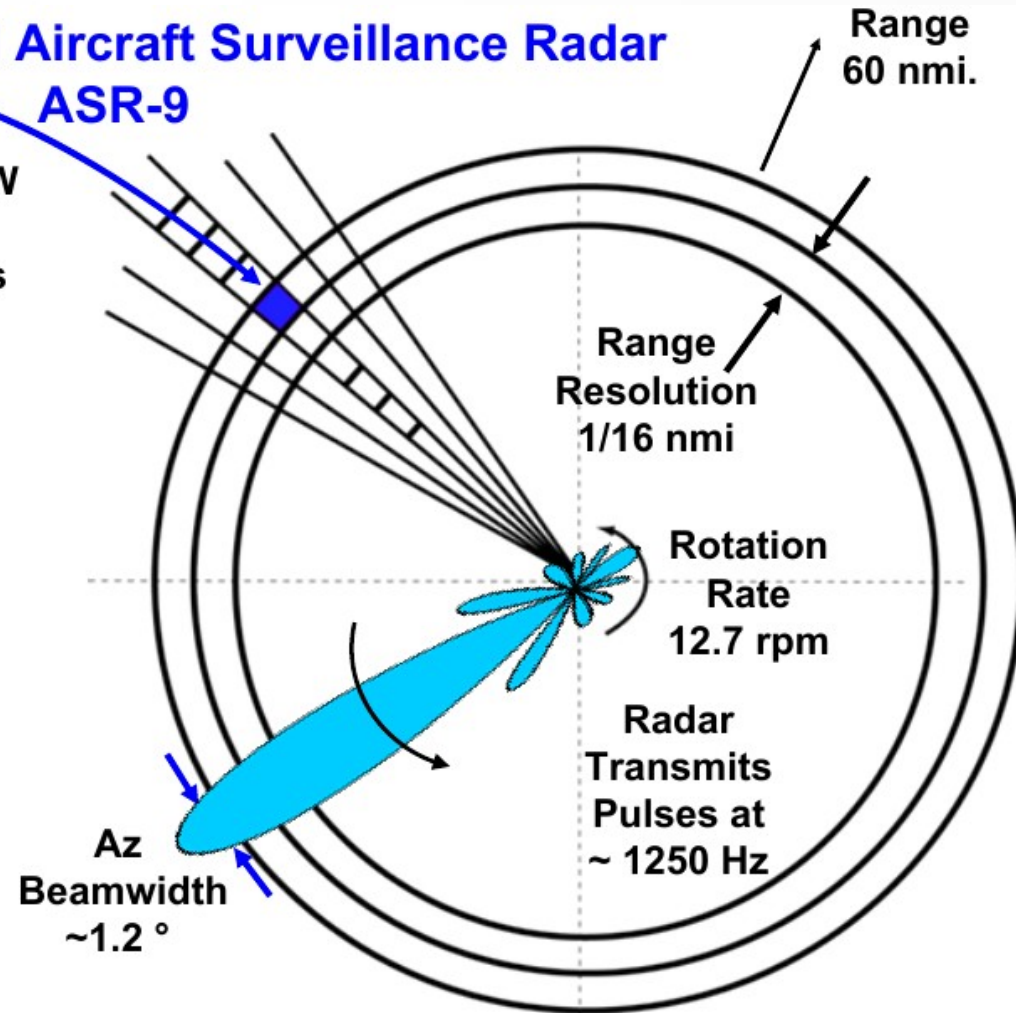
Example – Typical Aircraft Surveillance Radar ASR-9



As Antenna Rotates
~22 pulses / Beamwidth

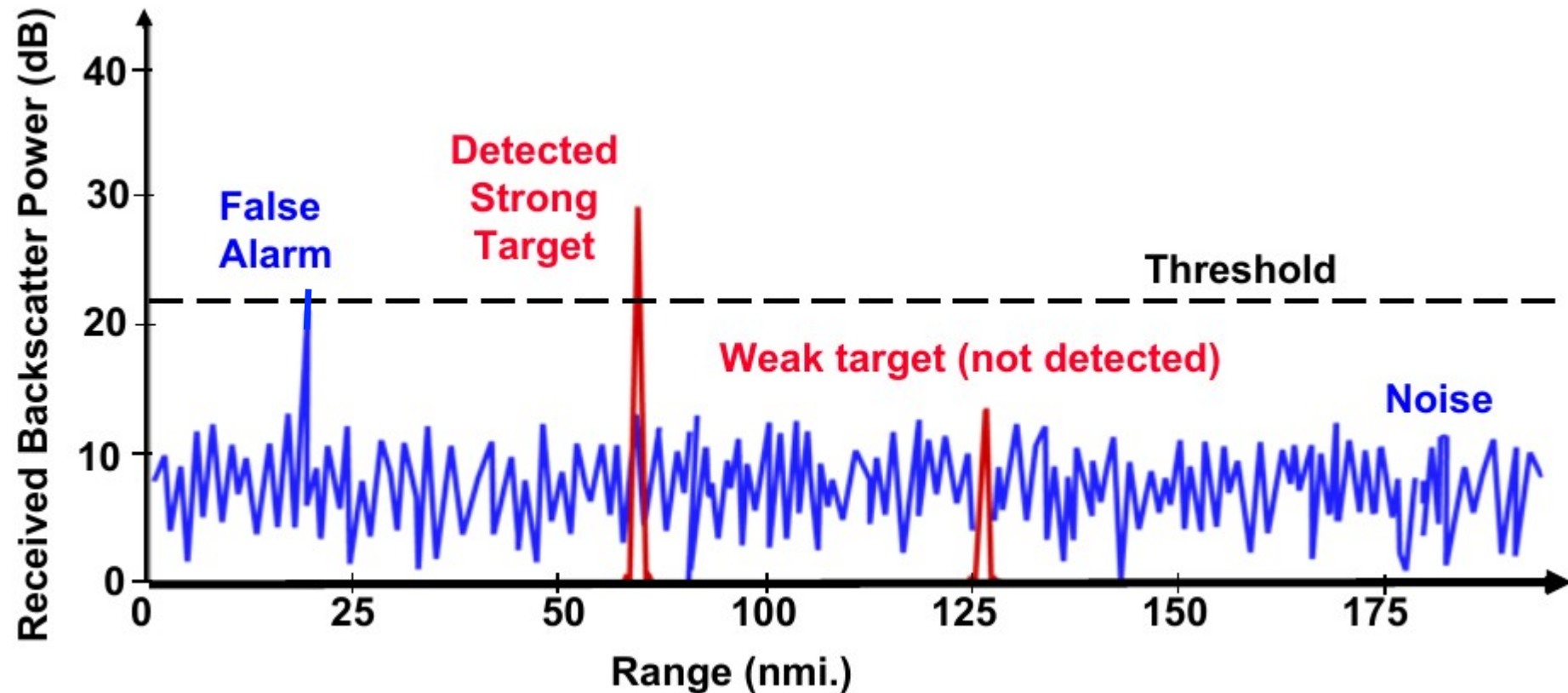
Range - Azimuth - Doppler Cells

~1000 Range cells
~500 Azimuth cells
~8-10 Doppler cells
5,000,000 Range-Az-Doppler Cells
to be threshold every 4.7 sec.



Is There a Target Present
in Each Cell?

Target Detection in Noise



- Received background noise and target echo fluctuate randomly → Both are random variables
- To decide if a target is present, at a given range, we need to set a threshold (constant or variable)
- Detection performance (**Probability of Detection, P_d**) depends of the strength of the target relative to that of the noise and the threshold setting (**Signal-To Noise Ratio** and **Probability of False Alarm, P_{fa}**)

Signal Detection

- Decision about target presence for each evaluated cell from measurement x
- Two hypotheses H_0, H_1
- Neyman-Pearson theorem/detector
 - Maximize P_D for chosen P_{fa}
- Based on information about characteristics of noise, clutter, signal

Statistics Theory	Radar Theory
Tested statistics $U(x)$ and threshold γ	Detector
Zero hypothesis H_0	Target absent, Noise only ($x=n$), PDF: $p(x H_0)$
Alternative hypothesis H_1	Target present, Signal+noise ($x=s+n$), PDF: $p(x H_1)$
1st case error (decision H_1 for real H_0)	False alarm, (P_{fa})
2nd case error (decision H_0 for real H_1)	Missed detection, ($1-P_D$)

Optimum Threshold Test

		Decision	
		H_0	H_1
Reality	H_0	Do not report	False alarm
	H_1	Missed detection	Detection

Probability of Detection:

P_D Probability we choose H_1 for reality H_1

Probability of False alarm:

P_{fa} Probability we choose H_1 for reality H_0

Neyman-Pearson criterion:

Maximize \mathbf{P}_D for \mathbf{P}_{fa} not greater than specified value

Likelihood function (ratio)

$$L(x) = \frac{p(x|H_1)}{p(x|H_0)} : \begin{array}{l} \geq T \rightarrow H_1 \\ < T \rightarrow H_0 \end{array}$$

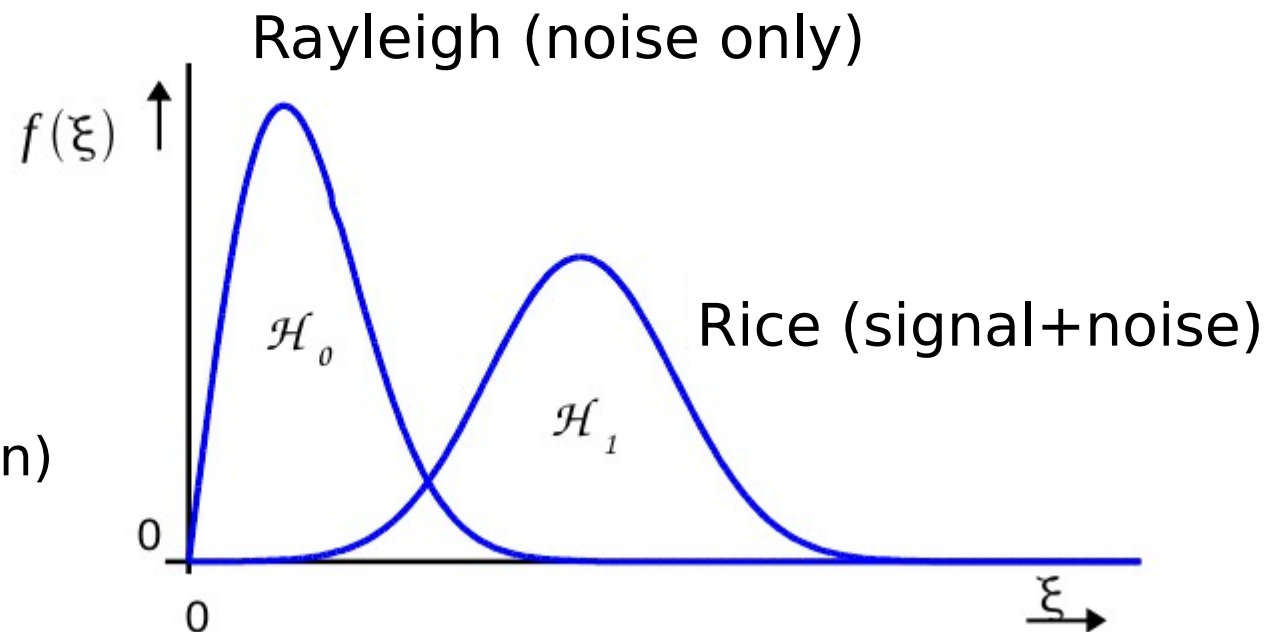
Threshold

Statistic description

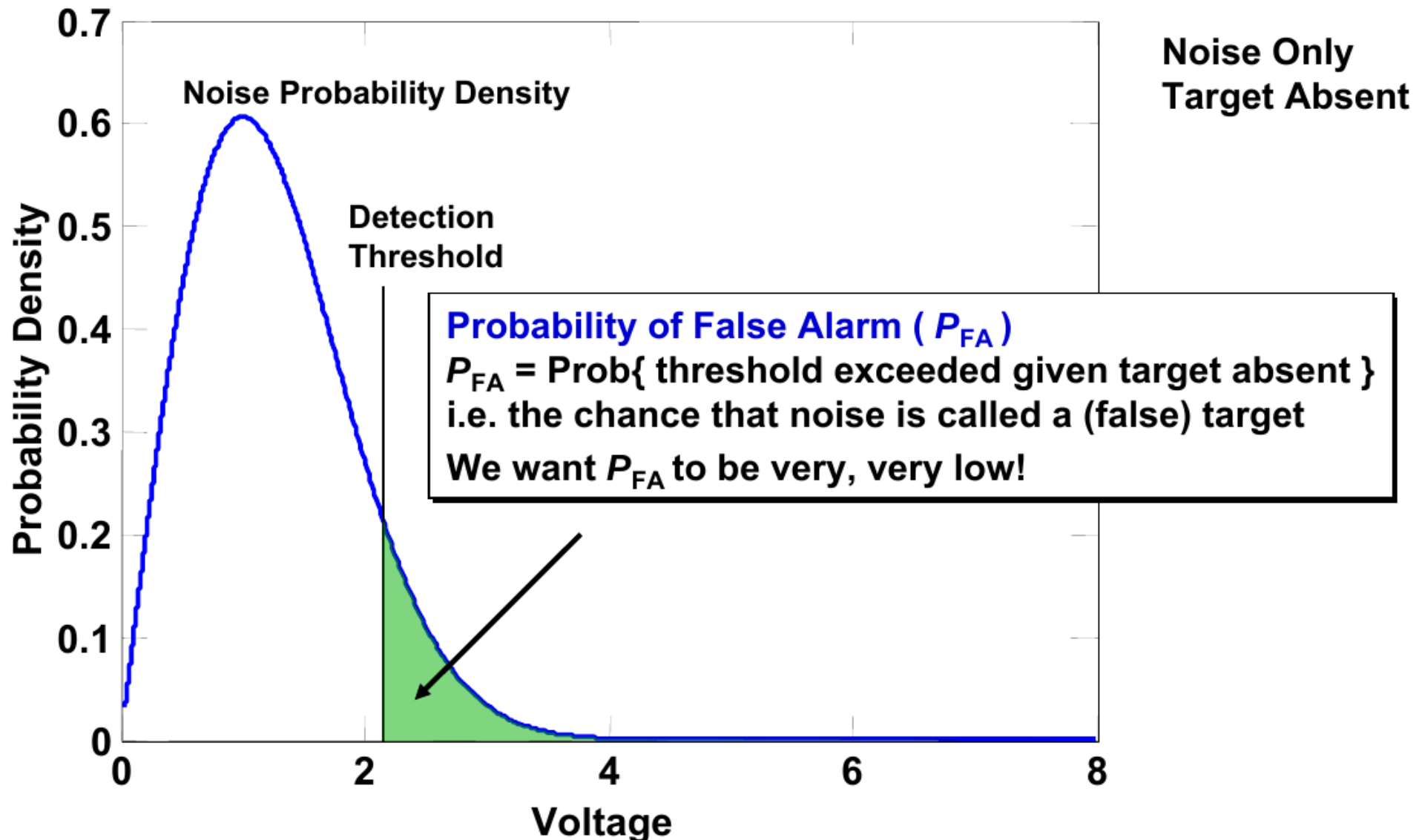
- Rayleigh distribution - noise probability density function (e.g. voltages)
- Rice distribution - signal+noise probability density function
- AWGN envelope and impacts of environment, non-fluctuating target

$$f(\xi|\mathcal{H}_0) = \frac{\xi}{\sigma^2} e^{-\frac{\xi^2}{2\sigma^2}}$$
$$f(\xi|\mathcal{H}_1) = \frac{\xi}{\sigma^2} e^{-\frac{\xi^2 + a^2}{2\sigma^2}} I_0\left(a\frac{\xi}{\sigma^2}\right)$$

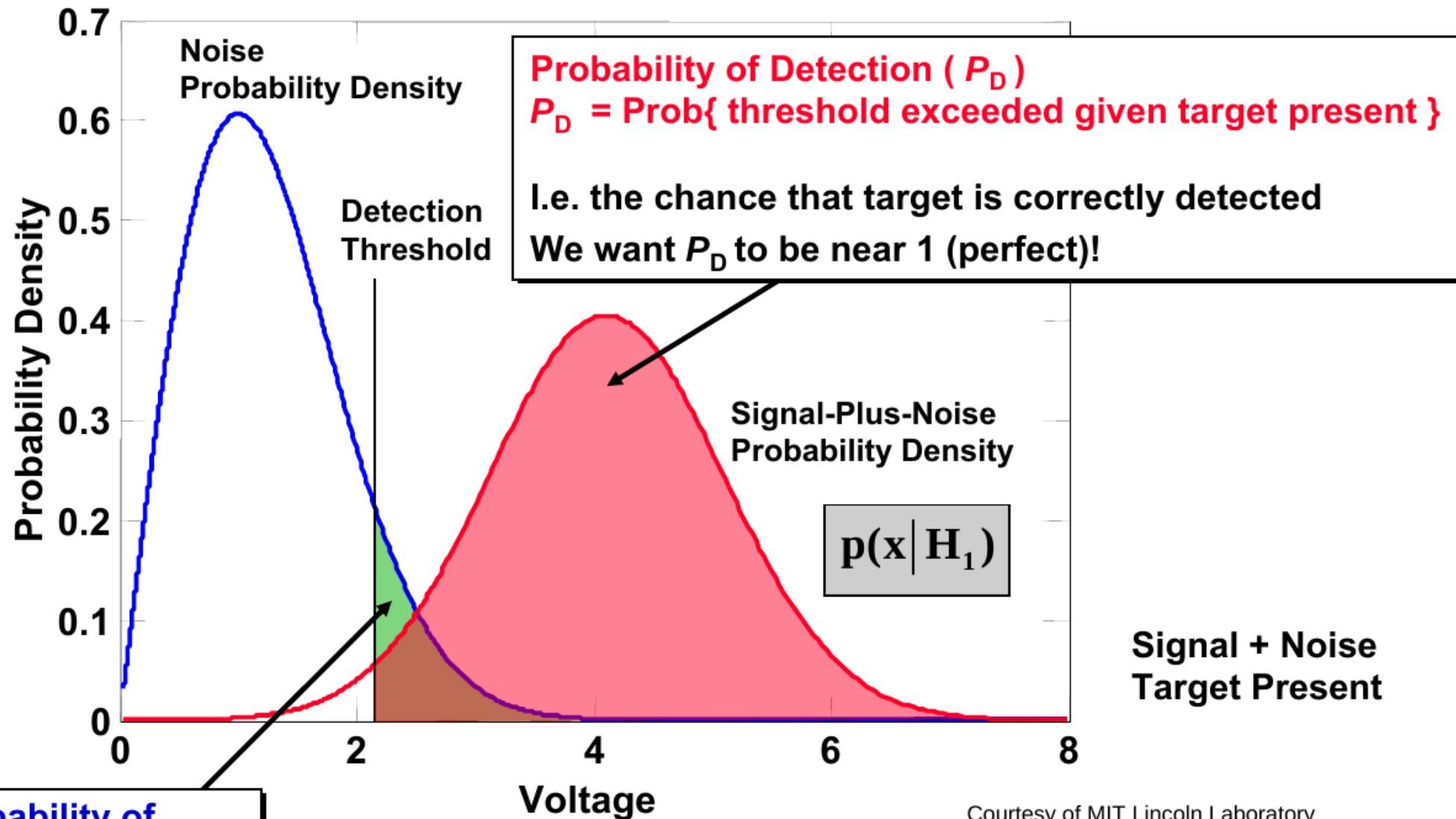
I_0 (modified Bessel function)



Detection statistics



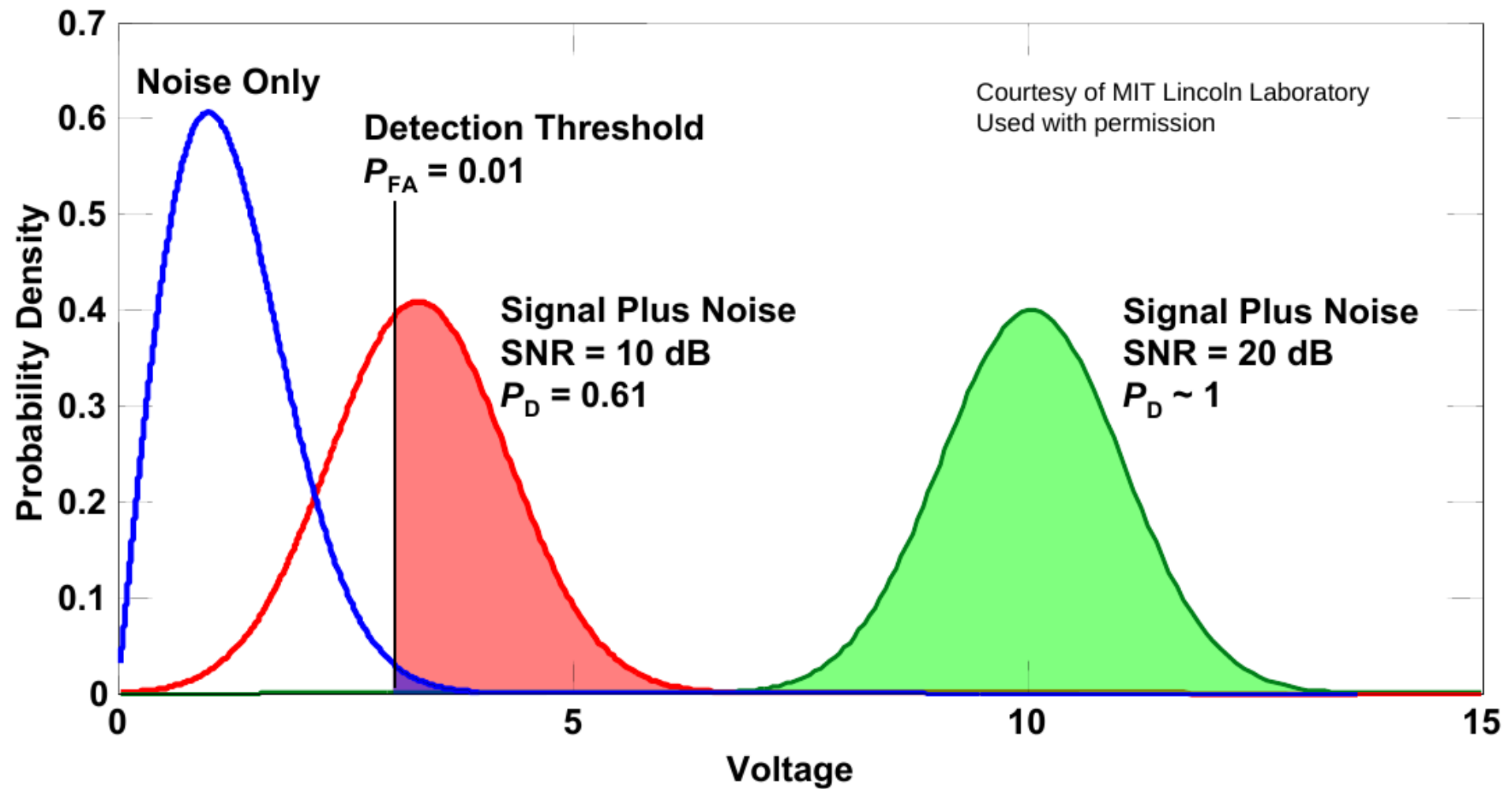
Detection statistics



**Probability of
False Alarm (P_{FA})**

Courtesy of MIT Lincoln Laboratory
Used with permission

Impact of SNR



P_D increases with SNR for given P_{fa} (threshold)

Non-fluctuating target detection

$$L(x) = \frac{P(x|\mathcal{H}_1)}{P(x|\mathcal{H}_0)} > T$$

$$P_{fa} = Pr\{L(x) > T; \mathcal{H}_0\} = \int_T^\infty p(\xi|\mathcal{H}_0) d\xi$$

$$P_d = Pr\{L(x) > T; \mathcal{H}_1\} = \int_T^\infty p(\xi|\mathcal{H}_1) d\xi$$

$$P_{fa} = \int_T^\infty \frac{\xi}{\sigma^2} e^{\frac{-\xi^2}{2\sigma^2}} d\xi = e^{\frac{-T^2}{2\sigma^2}}$$

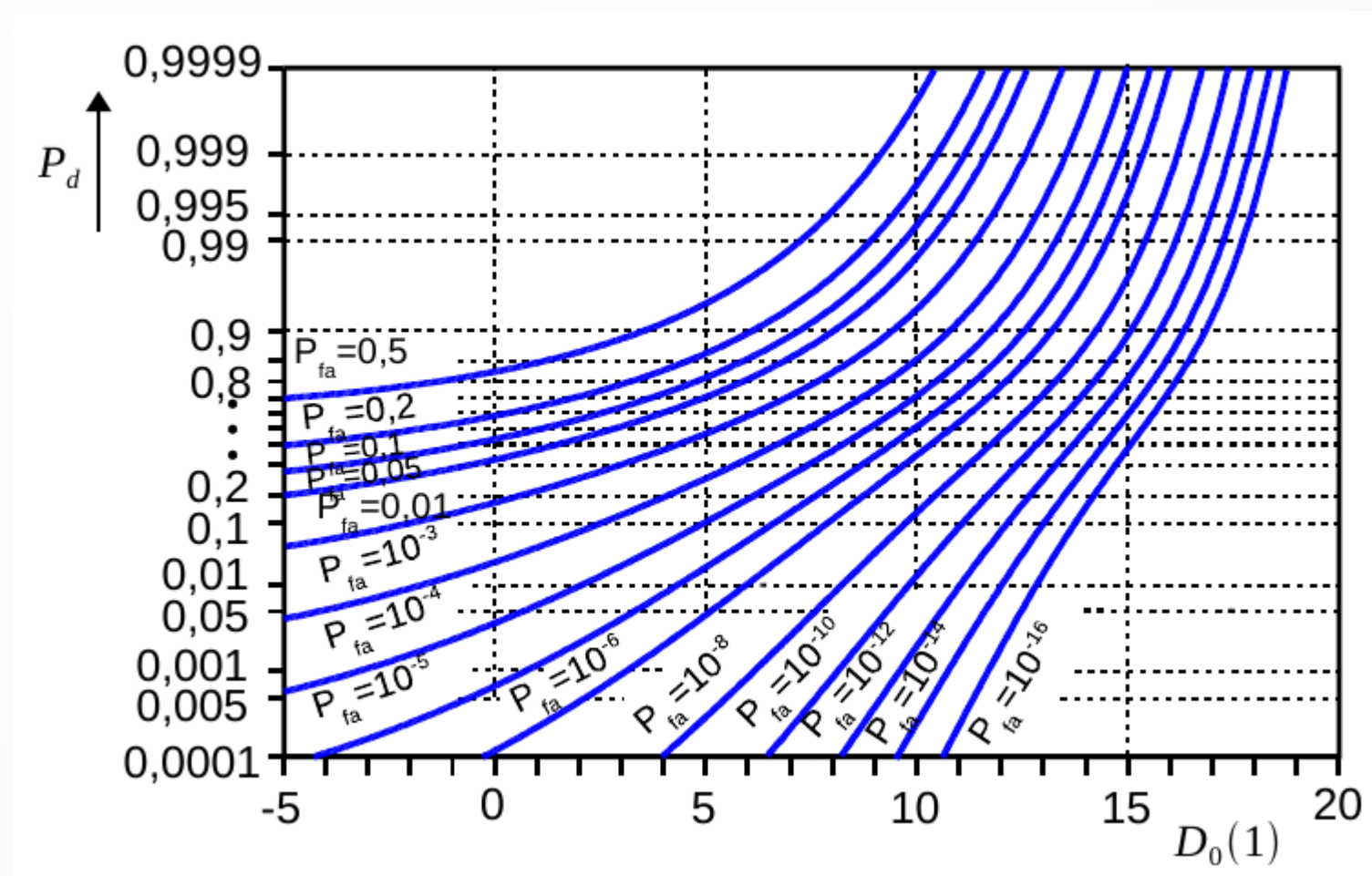
$$T = \sigma \sqrt{-2 \ln(P_{fa})}$$

$$S/N = \frac{s^2}{\sigma^2}$$

$$P_d = \int_T^\infty \frac{\xi}{\sigma^2} e^{\frac{-\xi^2 + s^2}{2\sigma^2}} I_0\left(\frac{\xi s}{\sigma^2}\right) d\xi$$

Detection quality

- System parameters for required detection parameters
- Detection coefficient ($D_0(1)$ for pro SW0 – non-fluctuating target, single pulse detection)
 - Necessary SNR to reach P_d for given P_{fa}
 - Usual conditions
 - Non-fluctuating
 - $P_d = 0.9$; $P_{fa} = 10^{-6}$
 - Fluctuating
 - $P_d = 0.8$; $P_{fa} = 10^{-6}$



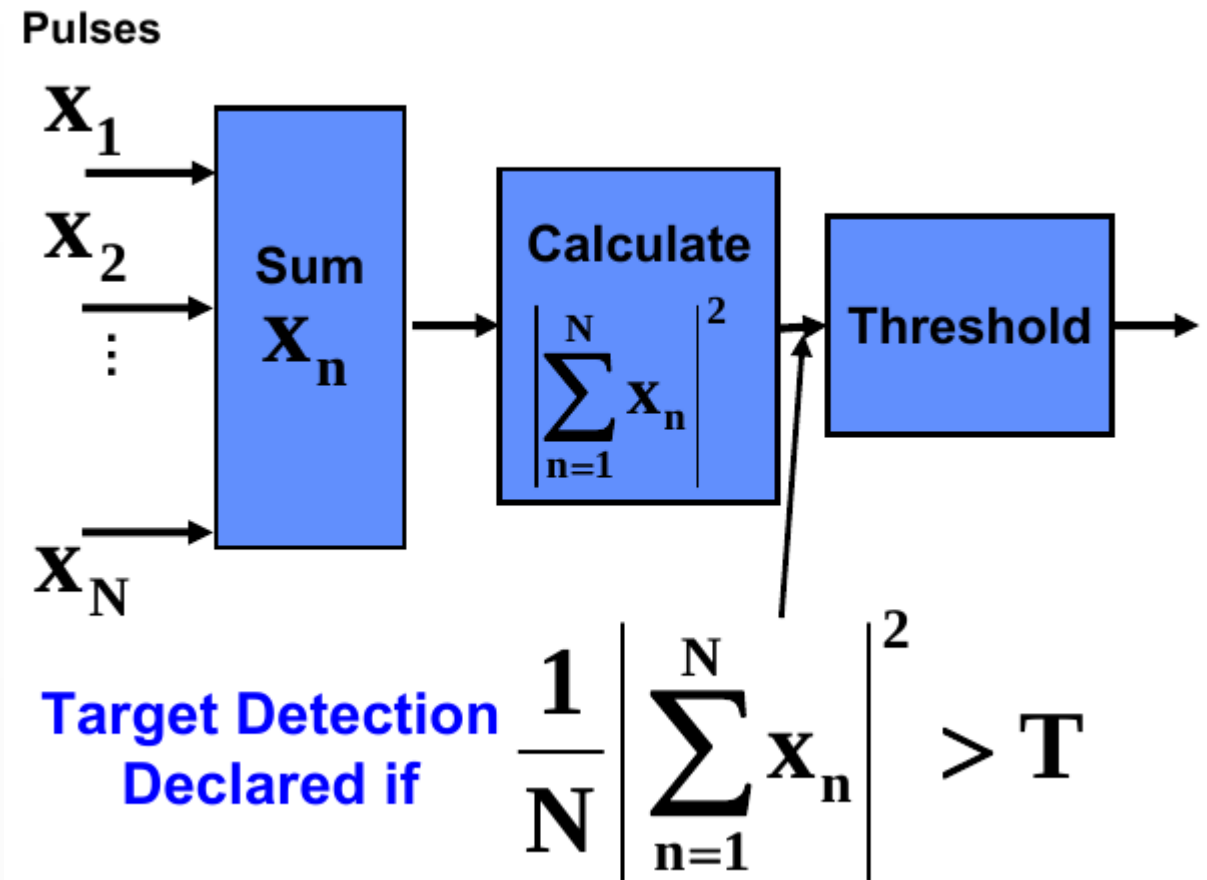
e.g. $P_d = 0.9$, $P_{fa} = 10^{-6}$, D_0 : SNR = 13.2 dB

Improvement by integration

- Use multiple pulses from same target
- Impact of statistical dependence of samples
- Motivation
 - Increase P_d
 - Decrease P_{fa}
 - Decrease of necessary SNR
- Detection
 - Single pulse
 - Multiple pulses
 - Coherent integration
 - Non-coherent (envelope, video) integration
 - Binary Integration (M of N)
 - Cumulative detection (1 of N)

Coherent integration

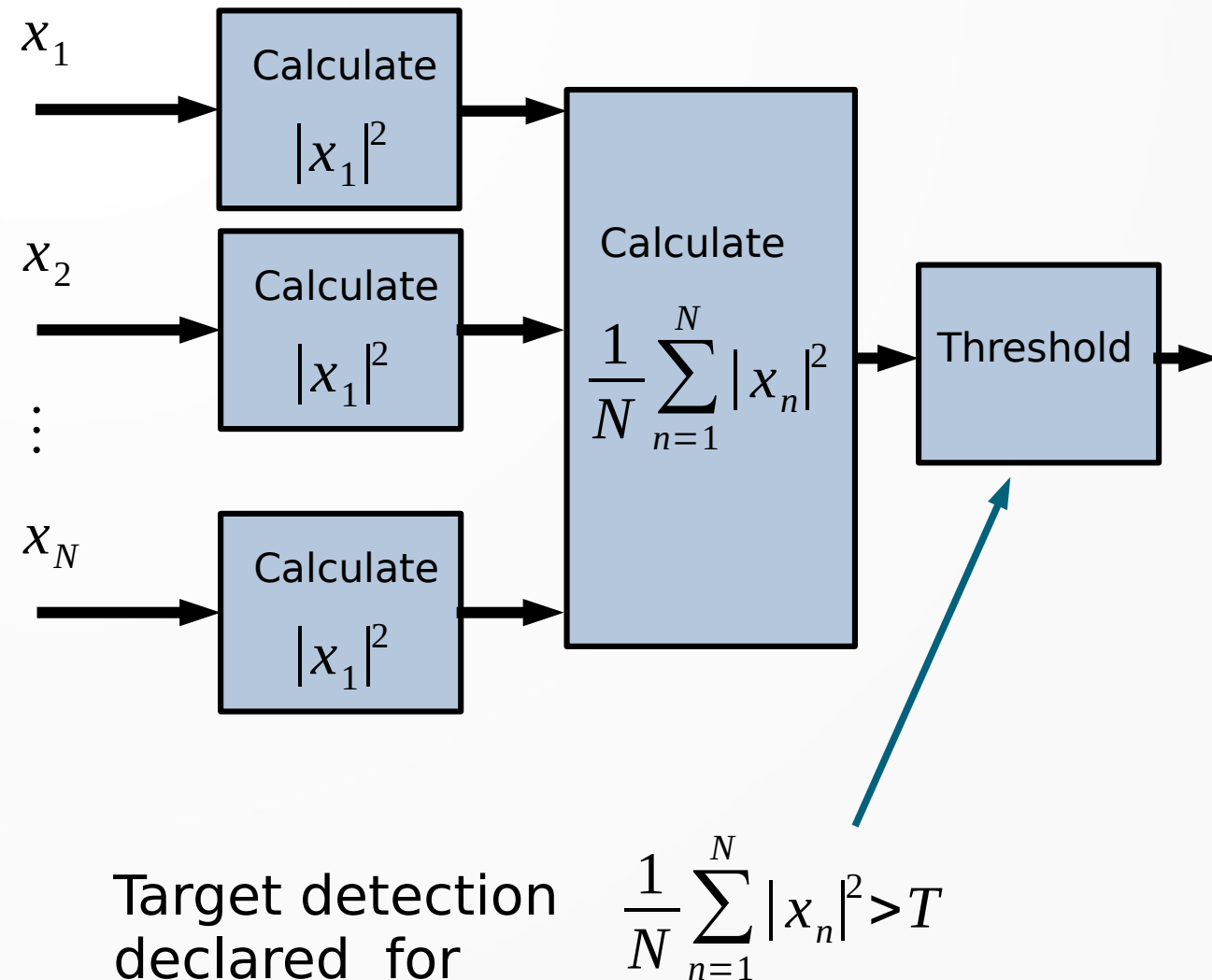
- Doppler compensation prior to integration (MTD)
- Integration (sum) of N pulses – samples of complex envelope
- Amplitude increase N -times
- Noise power (uncorrelated) increase by N -times
- SNR increase N -times
- Integration gain $G_i = N$



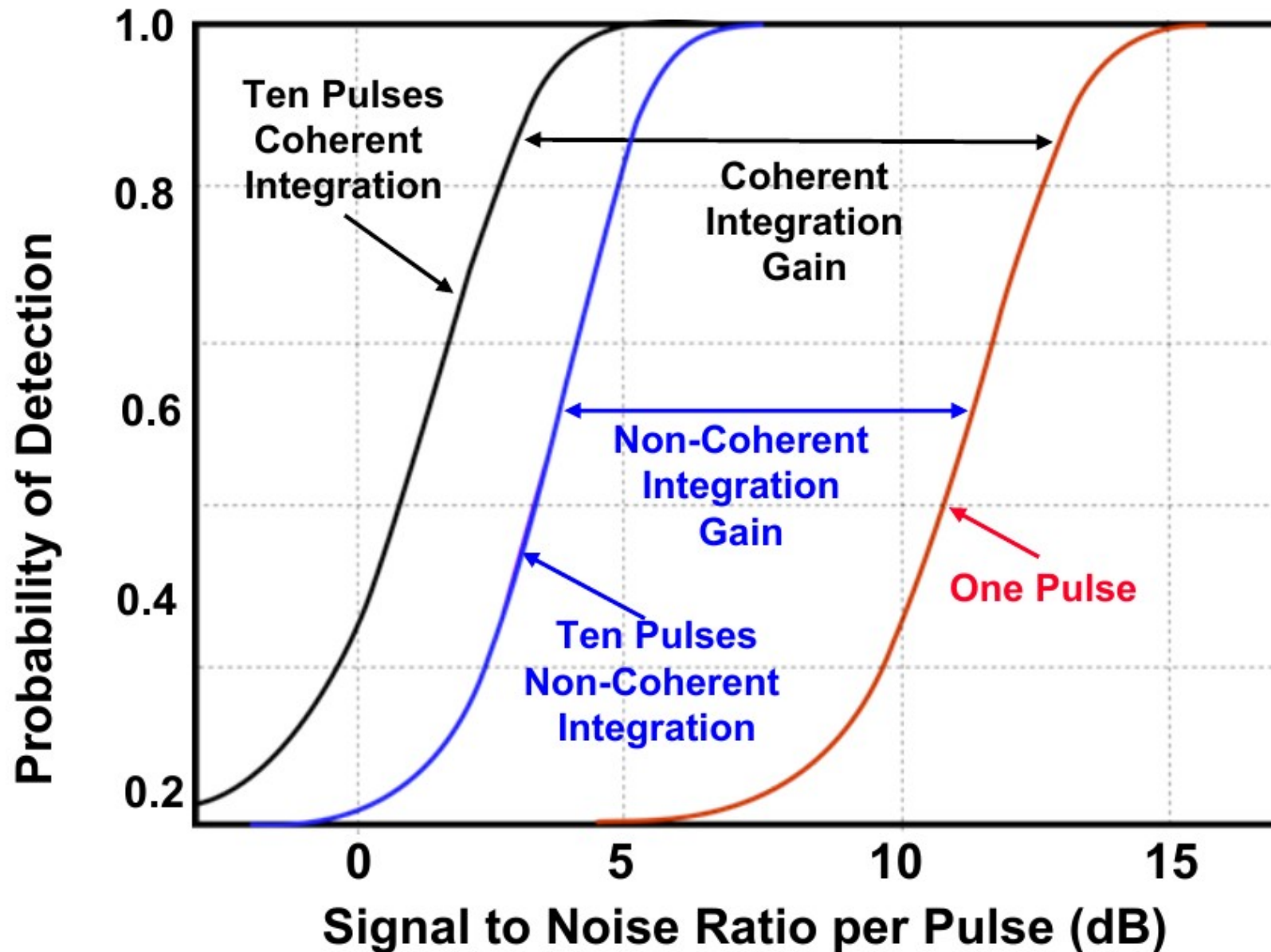
$$D_0(n) = \frac{D_0(1)}{G_i} = \frac{D_0(1)}{n}$$

Non-coherent Integration of envelope (video signal)

- Sum of amplitudes (powers)
- Ignores phase - simplification
- Envelope detector
- Higher SNR compared to coherent case
- Integration loses w.r.t. ideal (coherent) integrator



Coherent vs. Non-coherent Integration



**Steady
Target**

$$P_{FA} = 10^{-6}$$

Integration of binary output (M of N)

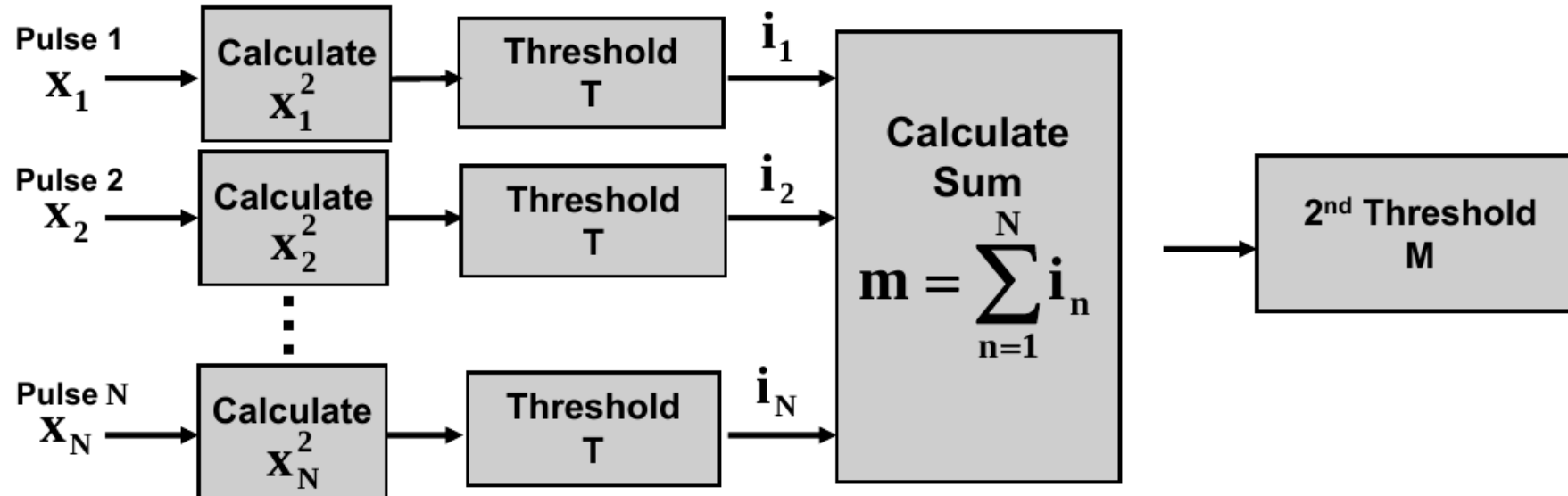
- Simplification of Detector realization
- Integration behind detector, count threshold binary outputs
- Secondary threshold for binary counts (M of N filter)
- First Detector can be set for higher P_{fa}

$$P_d = \sum_{k=m}^n \frac{n!}{k!(n-k)!} P_{d1}^k (1 - P_{d1})^{n-k}$$
$$P_{fa} = \sum_{k=m}^n \frac{n!}{k!(n-k)!} P_{fa1}^k (1 - P_{fa1})^{n-k}$$
$$P_{fa} \approx \frac{n!}{m!(n-m)!} P_{fa1}^m; P_{fa1} \ll 1$$

Can be found optimal
M for given N

$$m_{opt} \approx 1,5\sqrt{n}$$

M of N integration



Individual pulse detectors:

$$\begin{cases} |\mathbf{X}_n|^2 \geq T, & i_n = 1 \\ |\mathbf{X}_n|^2 < T, & i_n = 0 \end{cases}$$

2nd thresholding:

$$\begin{cases} m \geq M, & \text{target present} \\ m < M, & \text{target absent} \end{cases}$$

Target present if at least M detections in N pulses

Binary Integration

At Least M of N Detections

$$P_{M/N} = \sum_{k=M}^N \frac{N!}{k!(N-k)!} p^k (1-p)^{N-k}$$

Cumulative Detection

At Least 1 of N

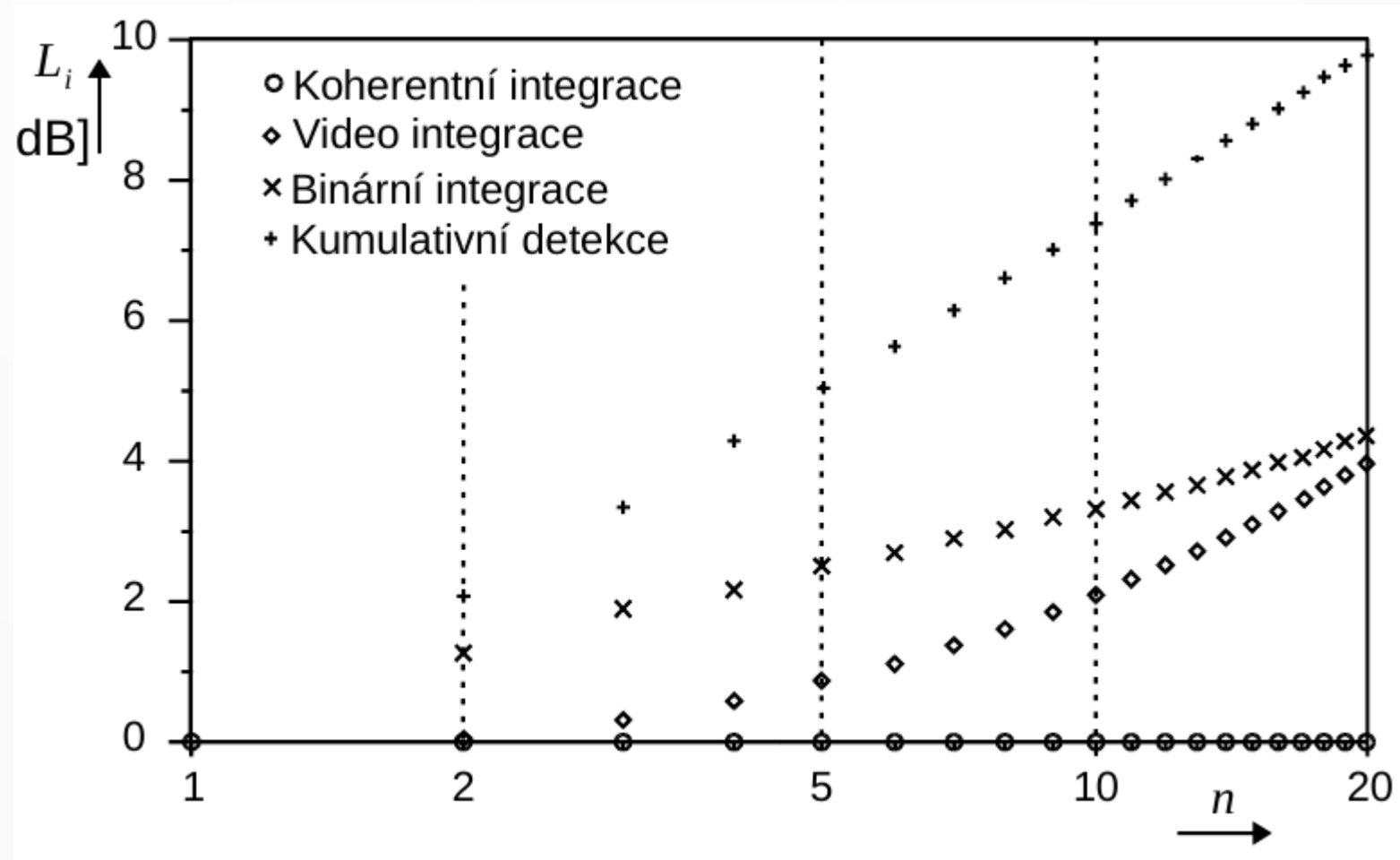
$$P_C = 1 - (1-p)^N$$

1 of N Detection – cumulative detection

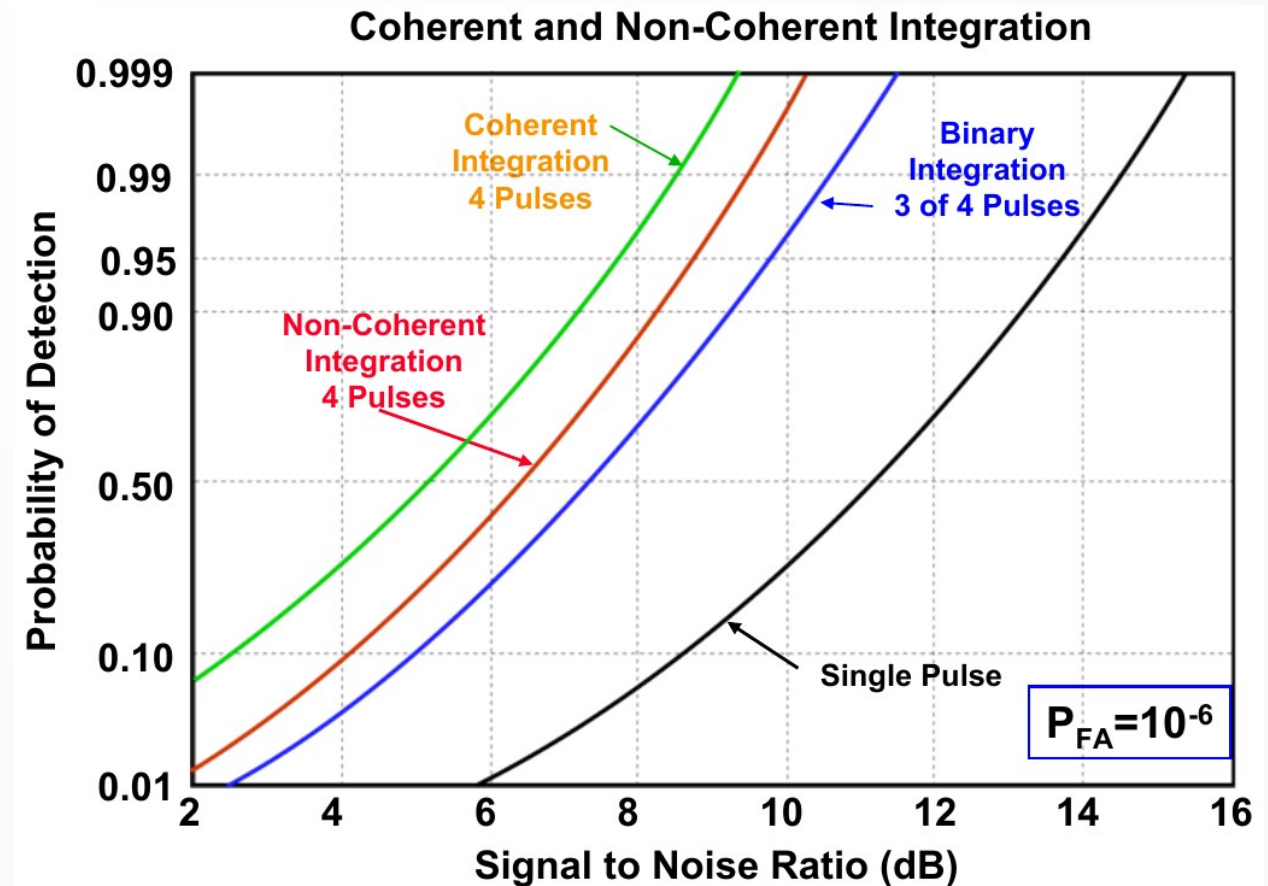
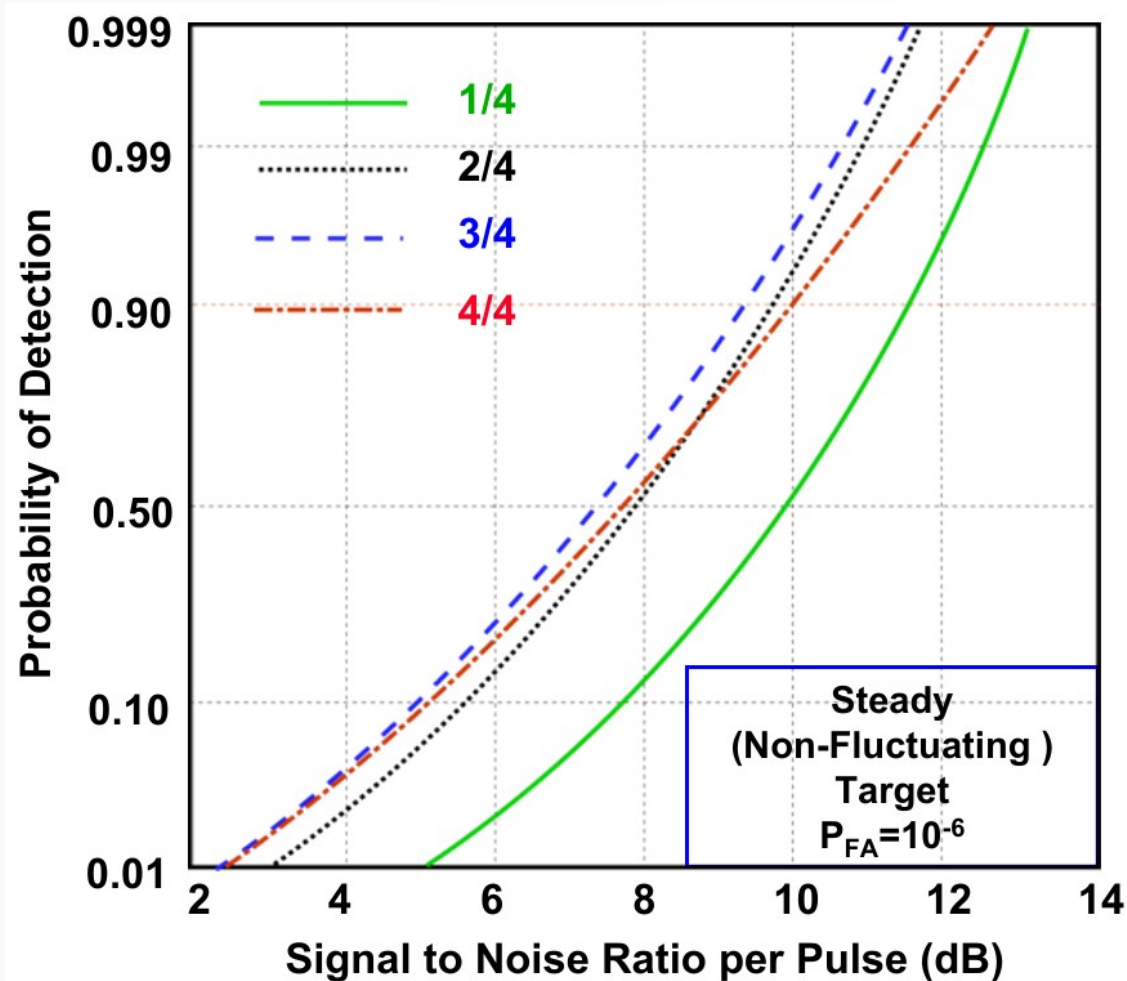
- N independent decisions for N pulses
- Detection positive if at least one of N decisions positive
- Higher requirements to P_{fa} setup in comparison to coherent and non-coherent integrations
- Little improvement of P_d compared to single pulse
→ low integration gain

$$P_D = 1 - (1 - P_{d1})^N$$

Loss by integration



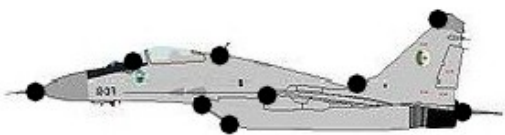
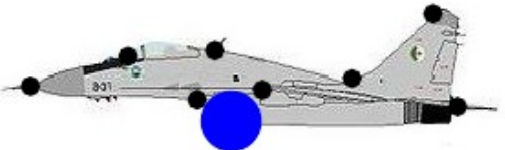
Detection comparison



Fluctuation of target (Fluctuation of RCS)

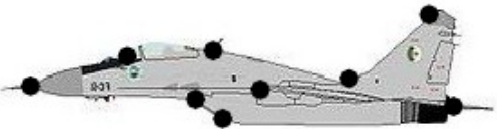
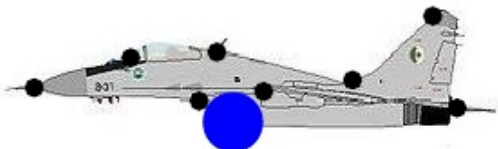
- Swerling models
- SW0 non-fluctuating (steady) target
- SW1 slow fluctuating target (scan to scan)
 - Rayleigh distribution of amplitudes, Exponential distribution of powers (RCS)
 - Mono-frequency radar observations example: Target consists from many comparable scatterers, no dominance
- SW2 fast fluctuating target (pulse to pulse)
 - SW1 target observed by agile radar
- SW3 slow fluctuating target (scan to scan)
 - Power distribution (RCS) χ^2 with 4 degrees of freedom (DOF)
 - Mono-frequency radar observations example: Target consists from one dominant scatterer and many secondary scatterers
- SW4 fast fluctuating target (pulse to pulse)
 - SW3 target observed by agile radar

Swerling Target Models

Nature of Scattering	RCS Model	Fluctuation Rate	
		Slow Fluctuation “Scan-to-Scan”	Fast Fluctuation “Pulse-to-Pulse”
Similar amplitudes 	Exponential (Chi-Squared DOF=2) $p(\sigma) = \frac{1}{\bar{\sigma}} \exp\left(-\frac{\sigma}{\bar{\sigma}}\right)$	Swerling I	Swerling II
One scatterer much Larger than others 	(Chi-Squared DOF=4) $p(\sigma) = \frac{4\sigma}{\bar{\sigma}^2} \exp\left(-\frac{2\sigma}{\bar{\sigma}}\right)$	Swerling III	Swerling IV

$\bar{\sigma}$ = Average RCS (m²)

Swerling Target Models

Nature of Scattering	Amplitude Model	Fluctuation Rate	
		Slow Fluctuation “Scan-to-Scan”	Fast Fluctuation “Pulse-to-Pulse”
Similar amplitudes 	Rayleigh $p(a) = \frac{2a}{\bar{\sigma}} \exp\left(-\frac{a^2}{\bar{\sigma}}\right)$	Swerling I	Swerling II
One scatterer much Larger than others 	Central Rayleigh, DOF=4 $p(a) = \frac{8a^3}{\bar{\sigma}^2} \exp\left(-\frac{2a^2}{\bar{\sigma}}\right)$	Swerling III	Swerling IV

$\bar{\sigma}$ = Average RCS (m²)

Impact of fluctuations to Probability of detection

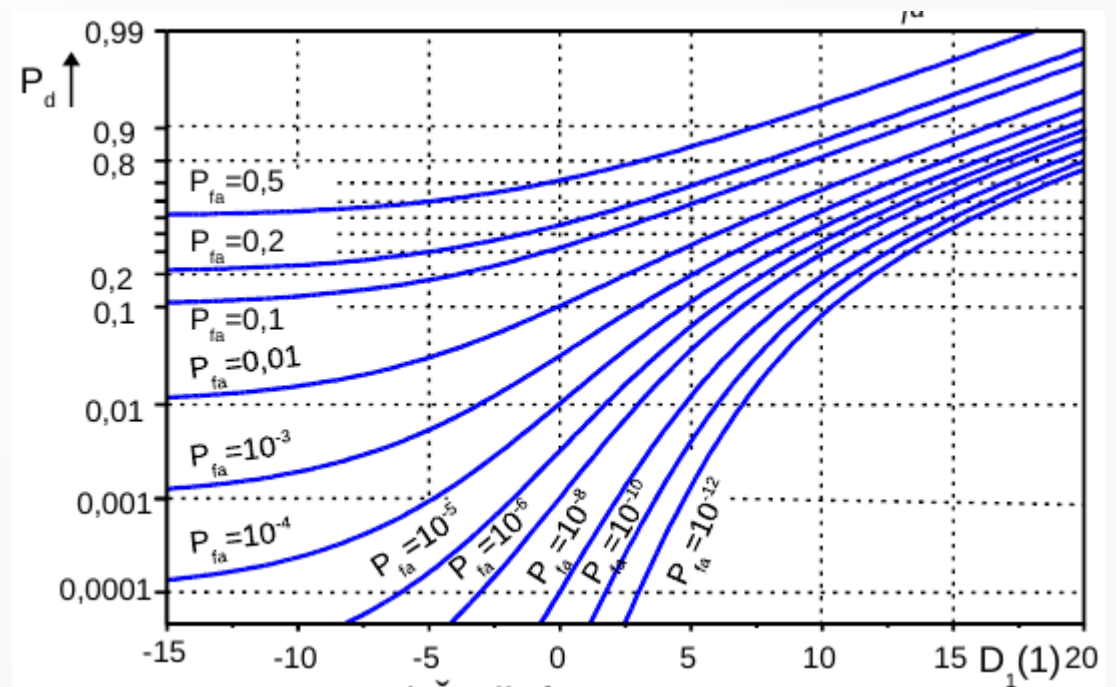
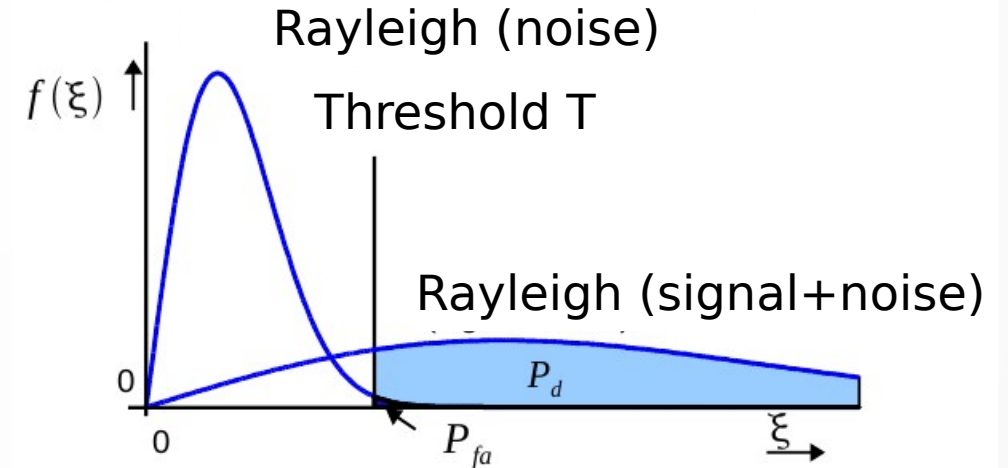
- PSD of fluctuating target echo – Rayleigh (non-fluctuating - Rice)

$$f_s(\xi|\mathcal{H}_1) = \frac{\xi}{\sigma^2 + \alpha^2} e^{\frac{-\xi^2}{2(\sigma^2 + \alpha^2)}}$$

$$P_d = e^{\frac{-T^2}{2(S+N)}} = e^{\frac{\ln(P_{fa})}{1+S/N}}$$

- Detection coefficient

$$D_1 = \frac{\ln P_{fa}}{P_d} - 1$$

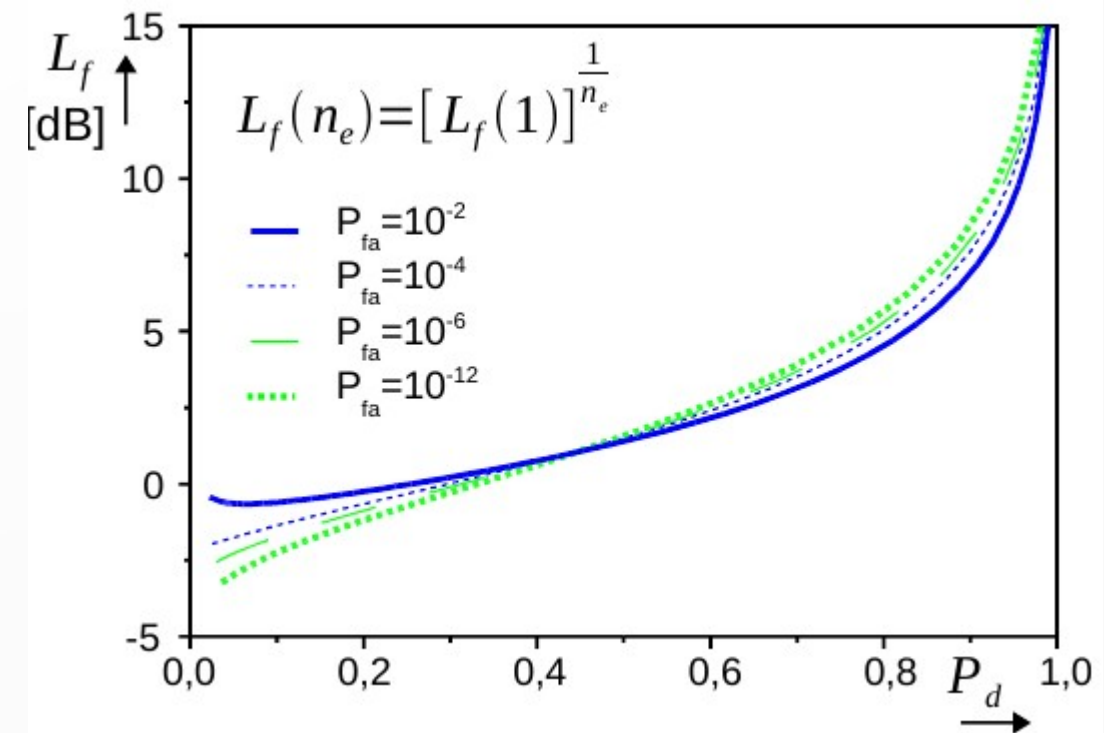


Fluctuation loss

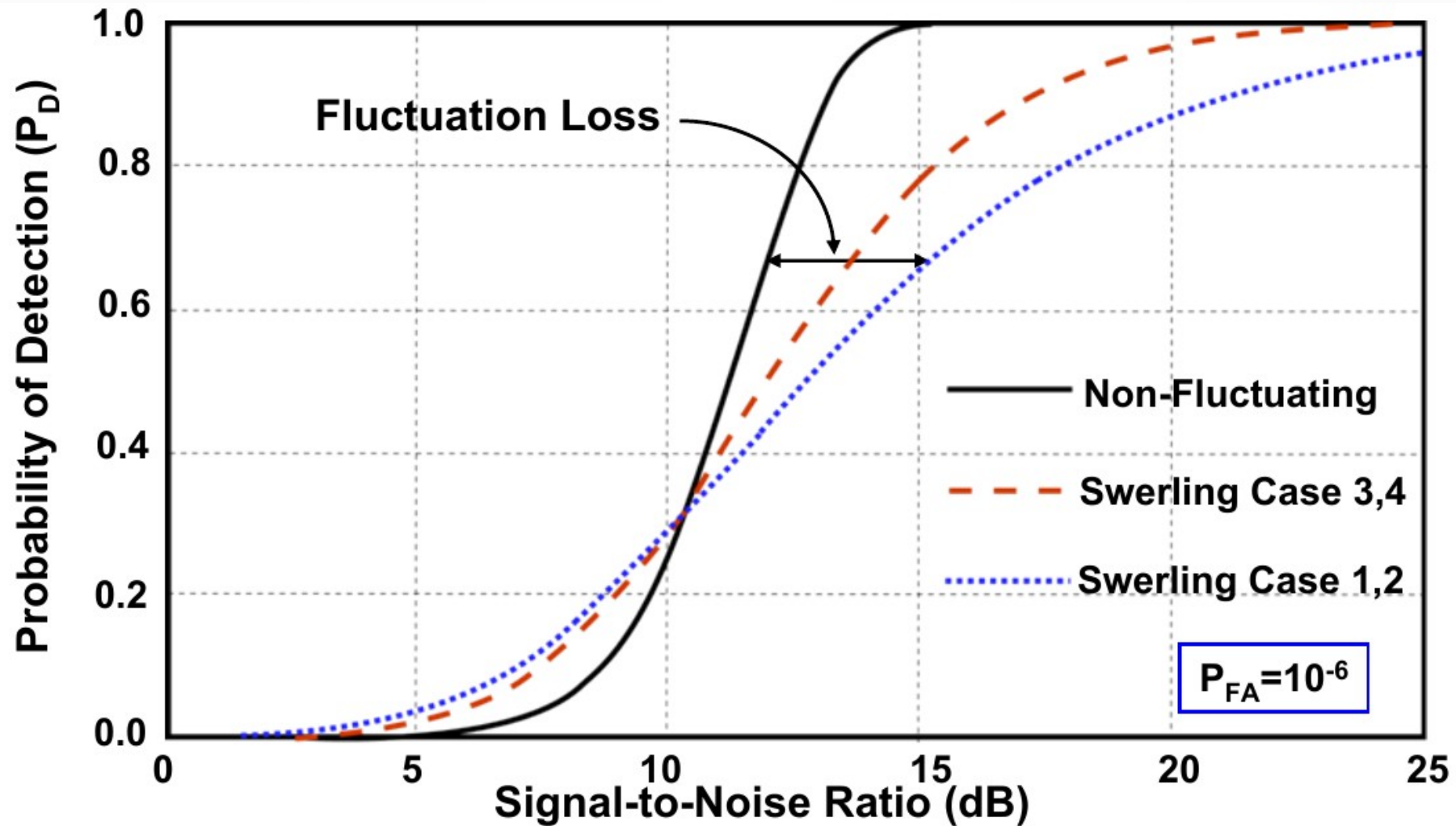
- SNR difference necessary to achieve same P_d for SW0 and (e.g.) SW1

$$L_f = \frac{D_1(1)}{D_0(1)}$$

- Integration of echoes from fluctuating targets
 - Dependent on mutual correlation of samples
- Diversity gain
 - time – observation time is longer than correlation length of samples
 - frequency (detection on more frequencies)

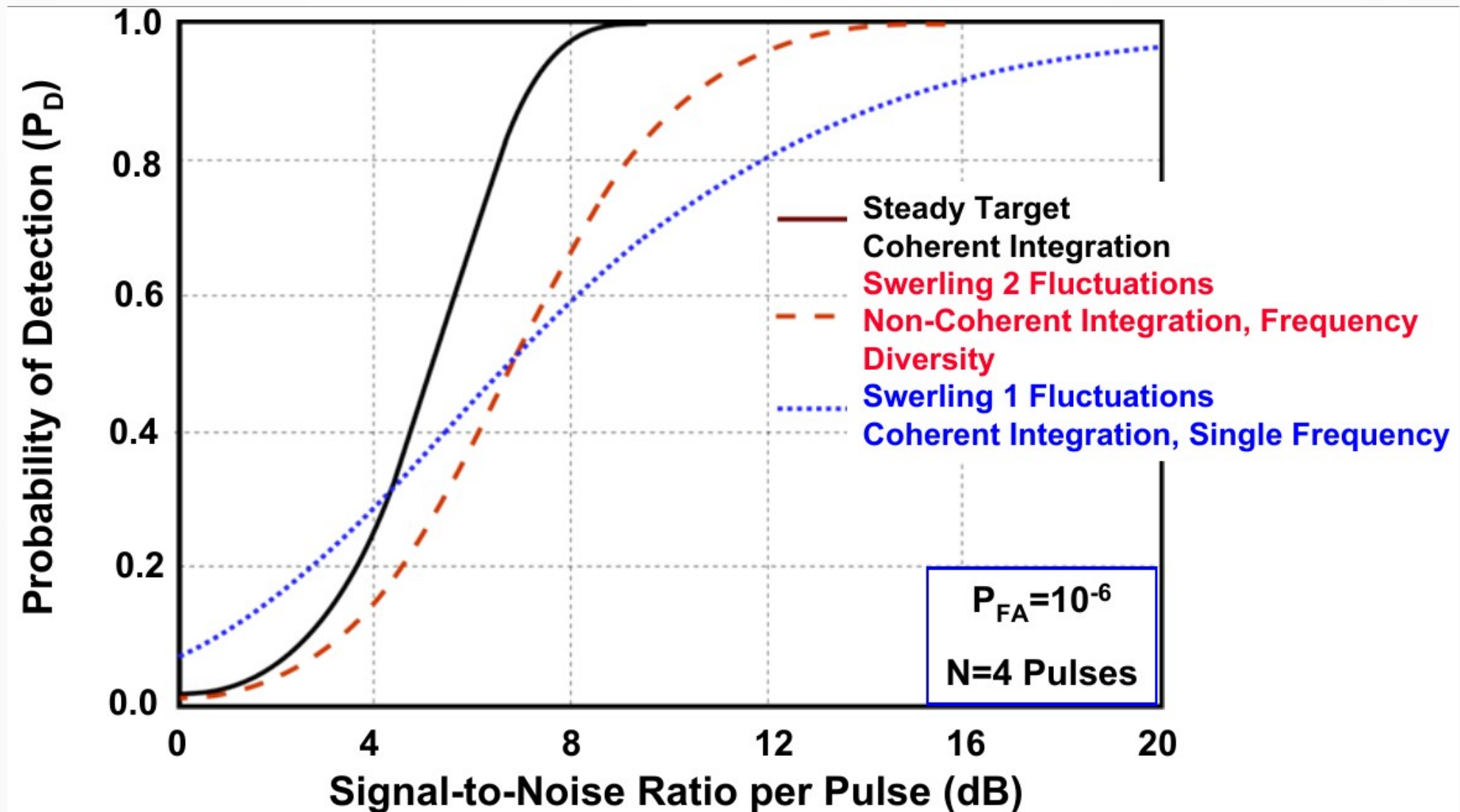


Fluctuation Loss



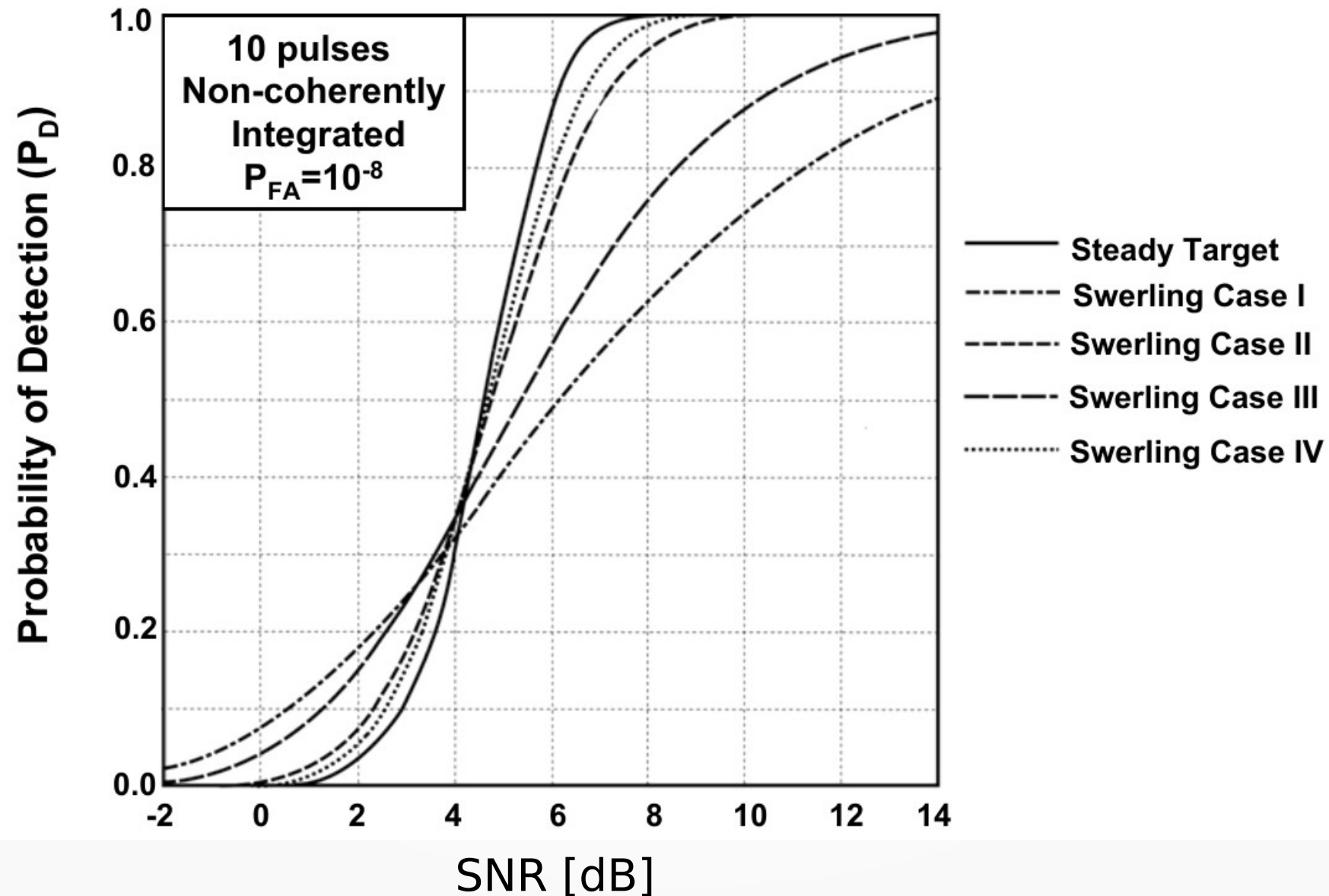
The fluctuation loss depends on the target fluctuations, probability of detection, and probability of false alarm.

Fluctuation Loss – Integration impact



For some targets (fast fluctuating), the non-coherent integration is better

Non-coherent integration for fluctuating targets



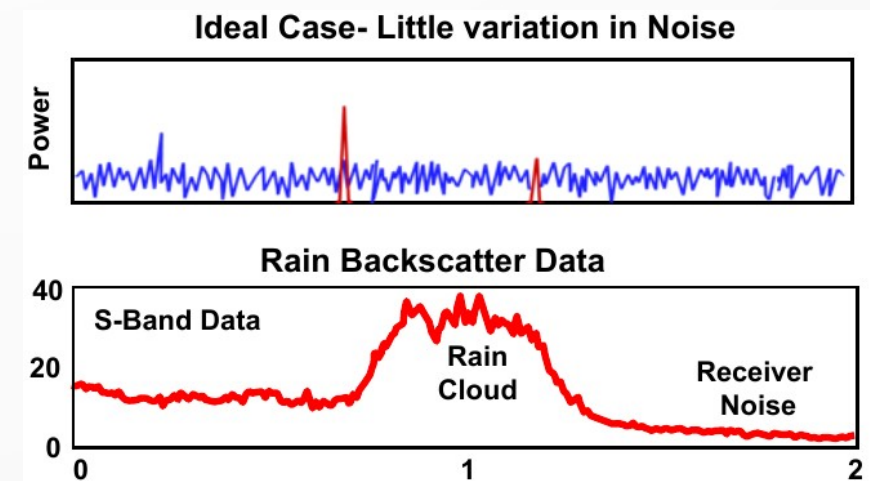
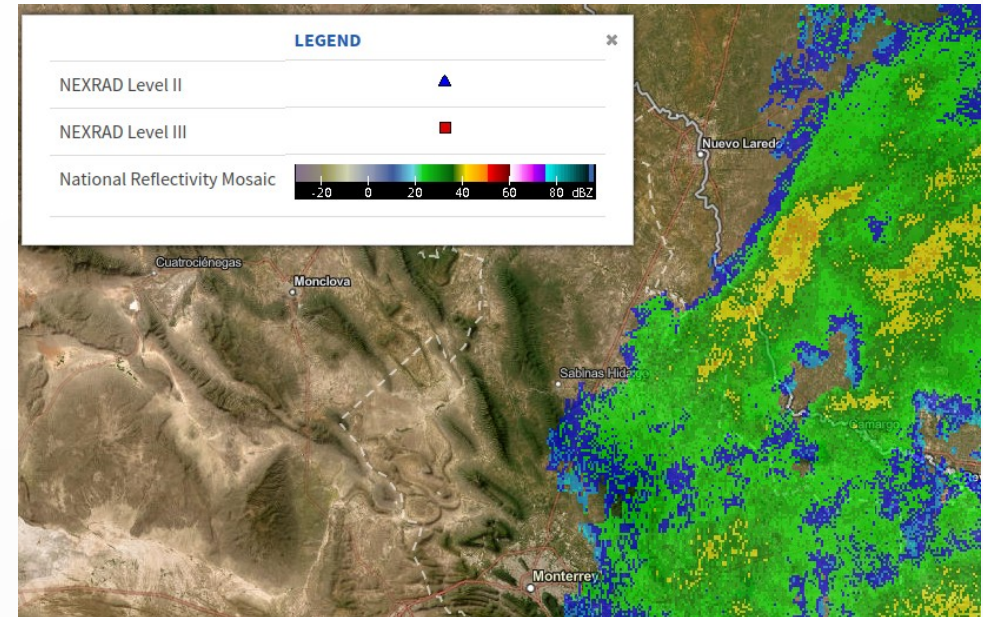
Other Fluctuation Models

- Detection Statistics Calculations
 - Steady and Swerling 1,2,3,4 Targets in Gaussian Noise
 - Chi- Square Targets in Gaussian Noise
 - Log Normal Targets in Gaussian Noise
 - Steady Targets in Log Normal Noise
 - Log Normal Targets in Log Normal Noise
 - Weibel Targets in Gaussian Noise
- Chi Square, Log Normal and Weibel Distributions have long tails
 - One more parameter to specify distribution
 - Mean to median ratio for log normal distribution
- When used
 - Ground clutter Weibel
 - Sea Clutter - Log Normal
 - HF noise - Log Normal
 - Birds - Log Normal

Adaptive detection - CFAR

Constant False Alarm Rate,
CFAR

- Adaptive estimation of the threshold to keep consistent (constant) P_{fa}
- Problems
 - Clutter borders
 - Clutter residuals
 - More targets
 - Interference, jamming
 - High sensitivity to model accuracy (statistics)

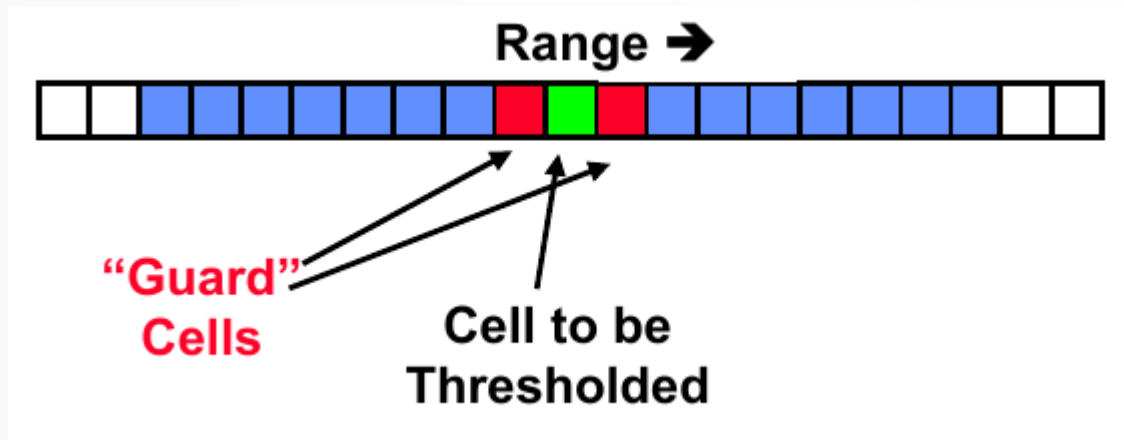


Adaptive detection - CFAR

- Realization
 - Parametric – e.g. CA (Cell Averaging) CFAR for Rayleigh
 - Non-parametric – ad hoc structures – logCACFAR, time averaging, median-based detector
- Rayleigh model suitable for
 - Amplitude based AWGN detection
 - Water reflections (vertical polarization)
 - Terrain reflections

CFAR Window

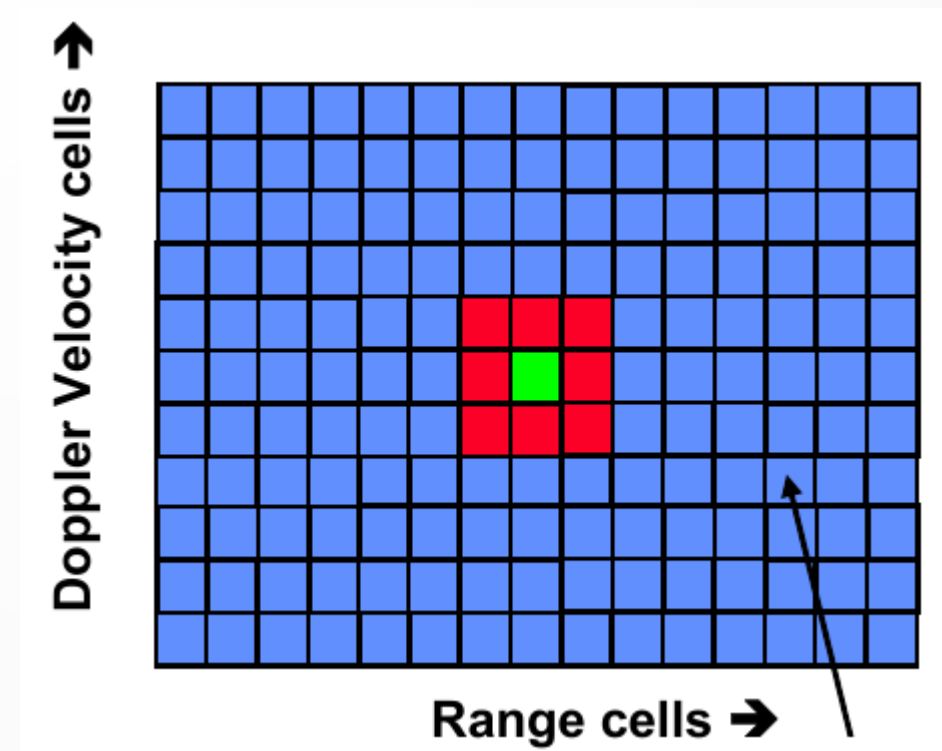
CFAR Window – Range cells



Estimate background mean from Range data only or Range/Doppler space data

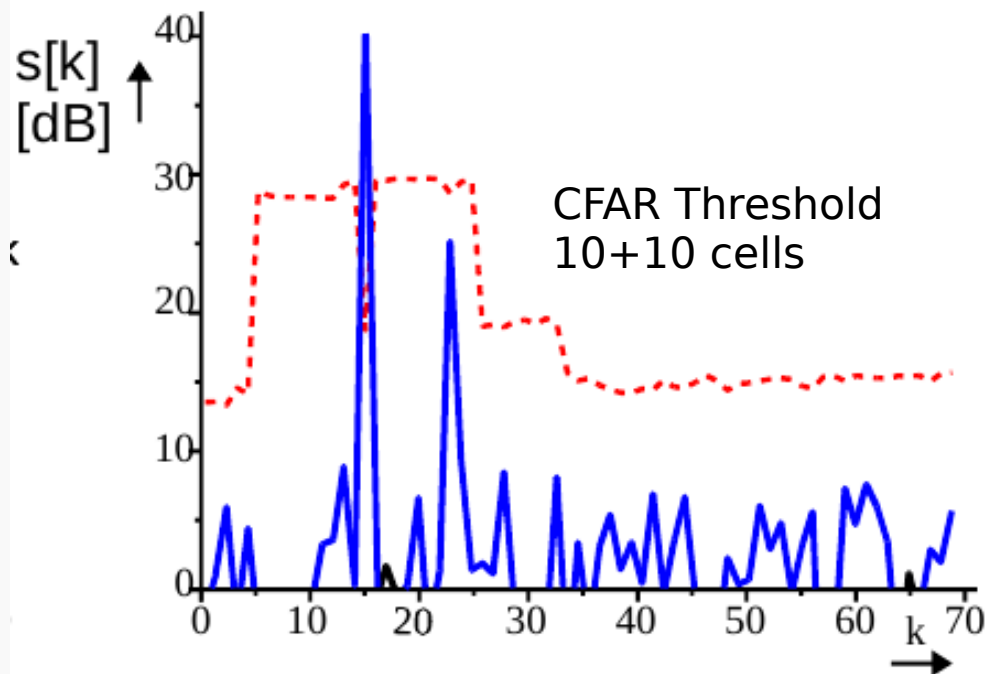
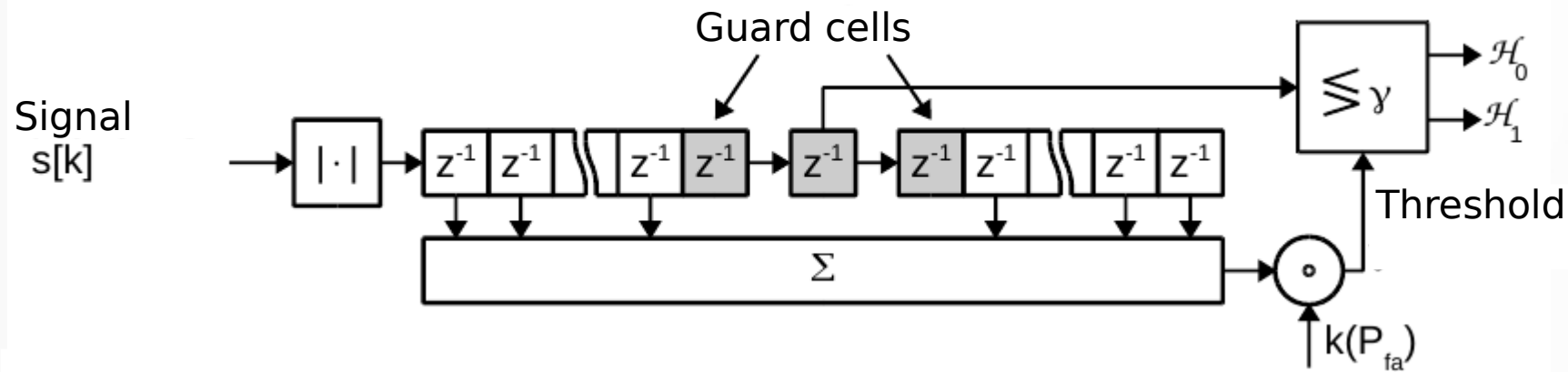
Set threshold as background mean multiplied by a constant (to adjust P_{fa})

CFAR Window – Range and Doppler cells



Blue cells for estimation of background and threshold

Adaptive detection – CA CFAR

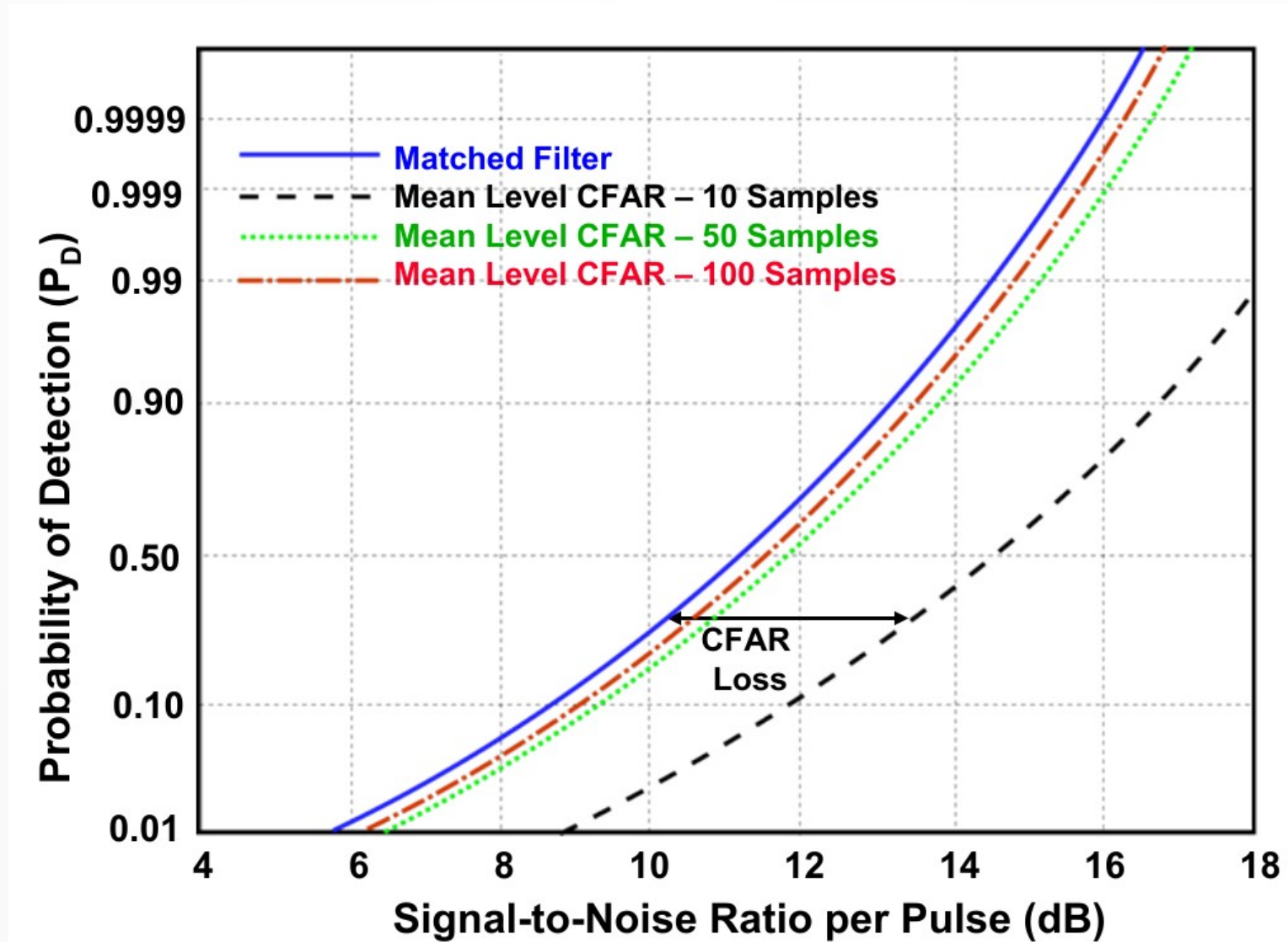


$$E[\xi] = \sigma \frac{\sqrt{\pi}}{2}$$

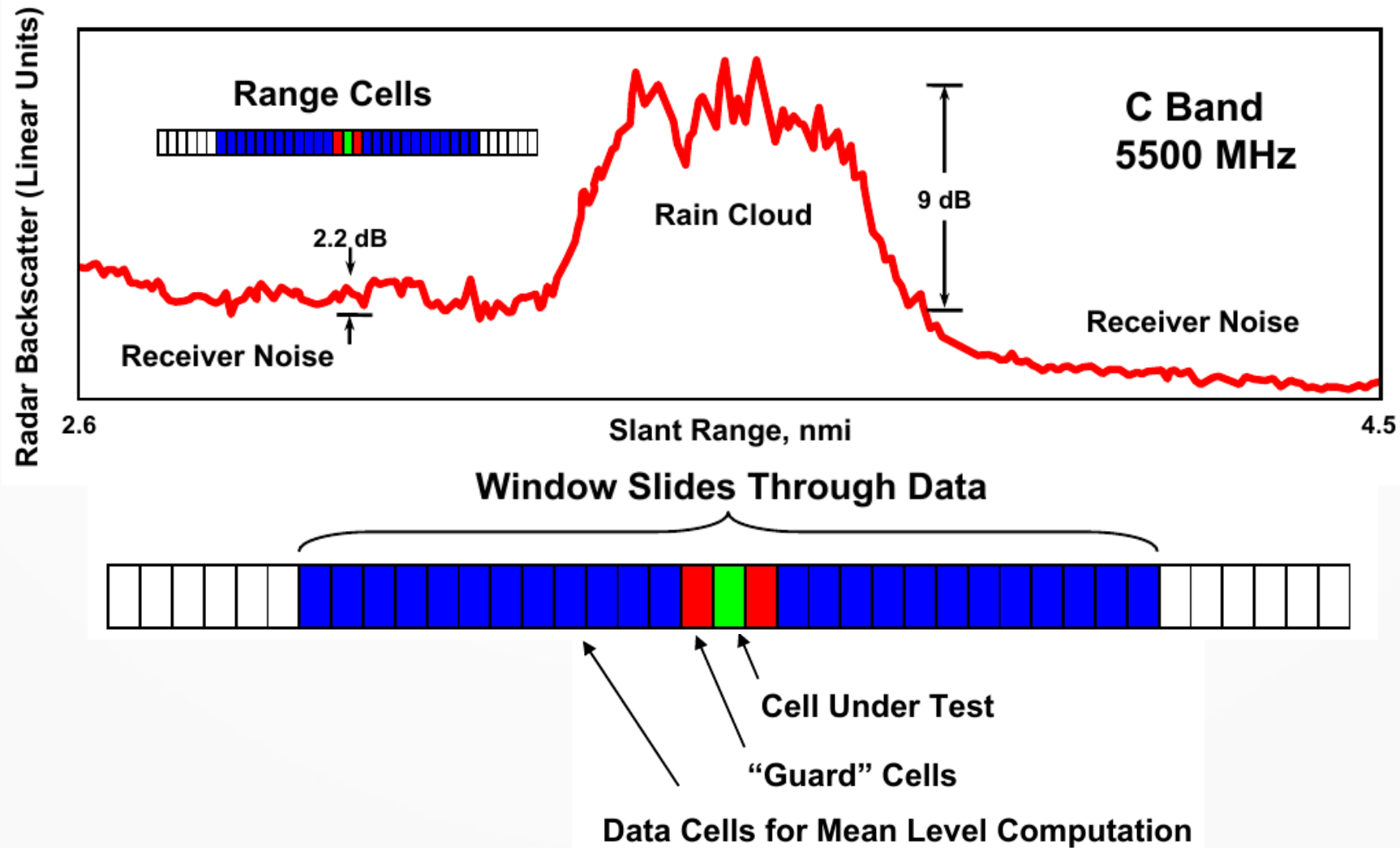
$$P_{fa} = \int_T^\infty \frac{\xi}{\sigma^2} e^{\frac{-\xi^2}{2\sigma^2}} d\xi = e^{\frac{-T^2}{2\sigma^2}}$$

$$T = \sigma \sqrt{-2 \ln(P_{fa})} = E[\xi] \sqrt{\frac{-4 \ln(P_{fa})}{\pi}}$$

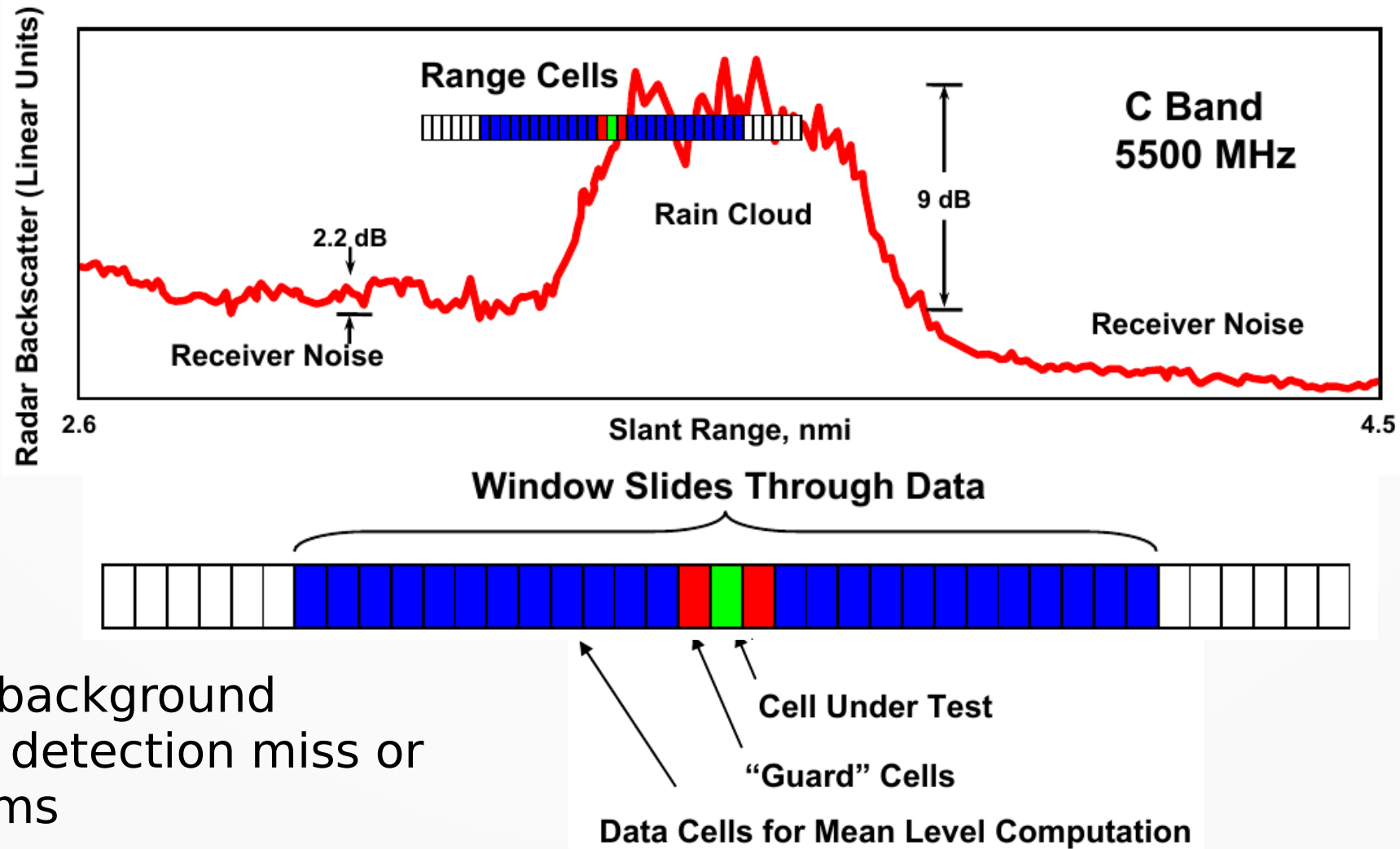
CA CFAR – impact of number of samples (cells)



Mean Level Threshold CFAR



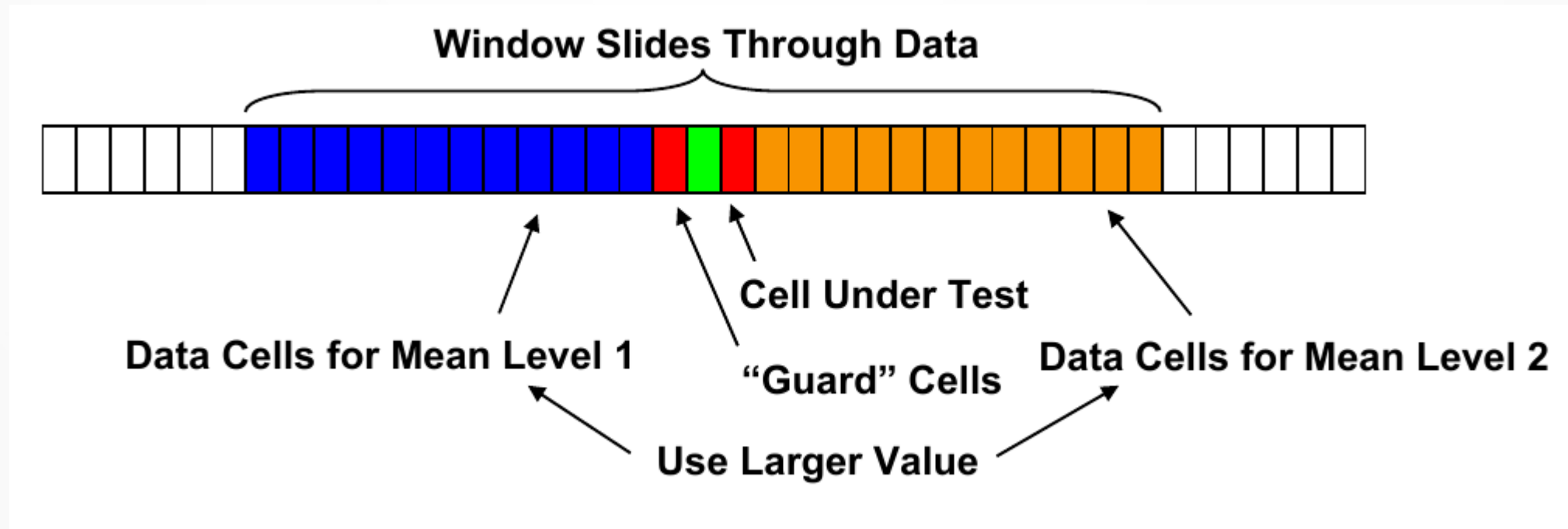
Mean Level Threshold CFAR



Mean for background increases detection miss or false alarms

Greatest of Means CFAR

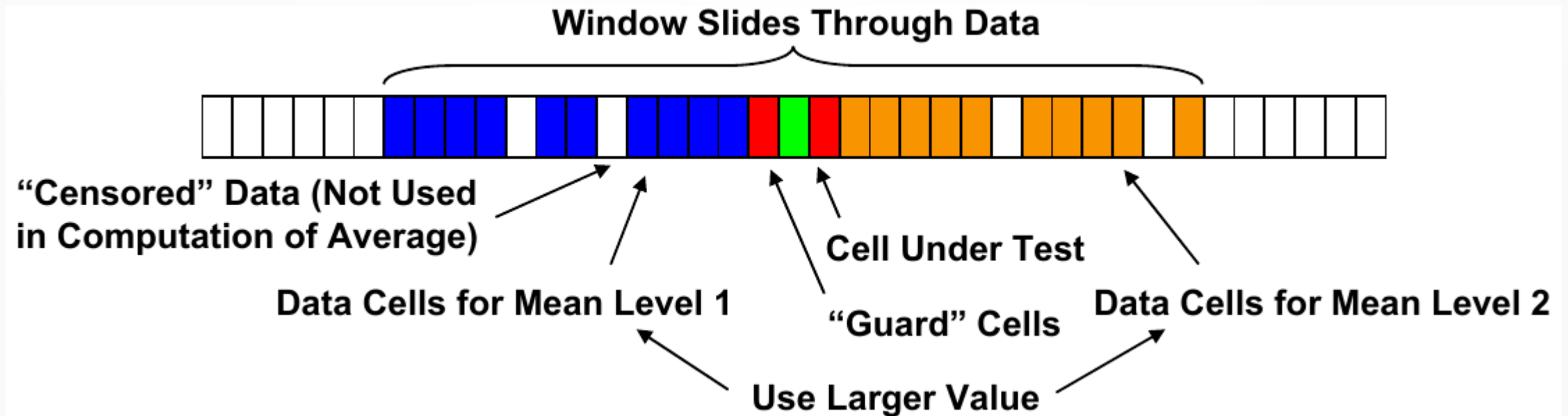
Compare mean value of $N/2$ cells before and after test cell and use larger value to determine threshold



- Helps reduce false alarms near sharp clutter or interference boundaries
- Nearby targets still raise threshold and suppress detection

Censored Greatest of Means CFAR

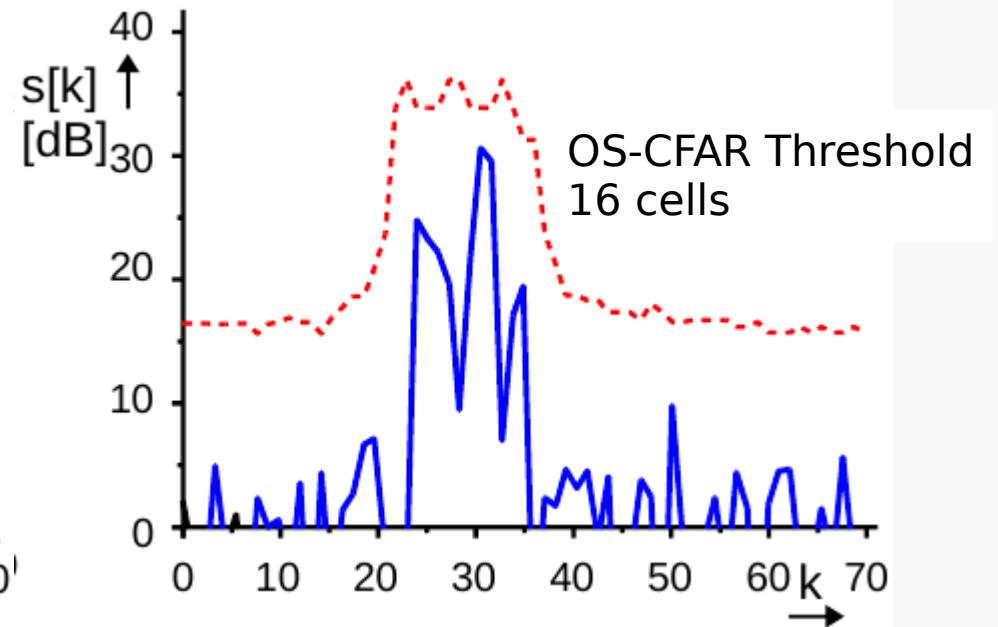
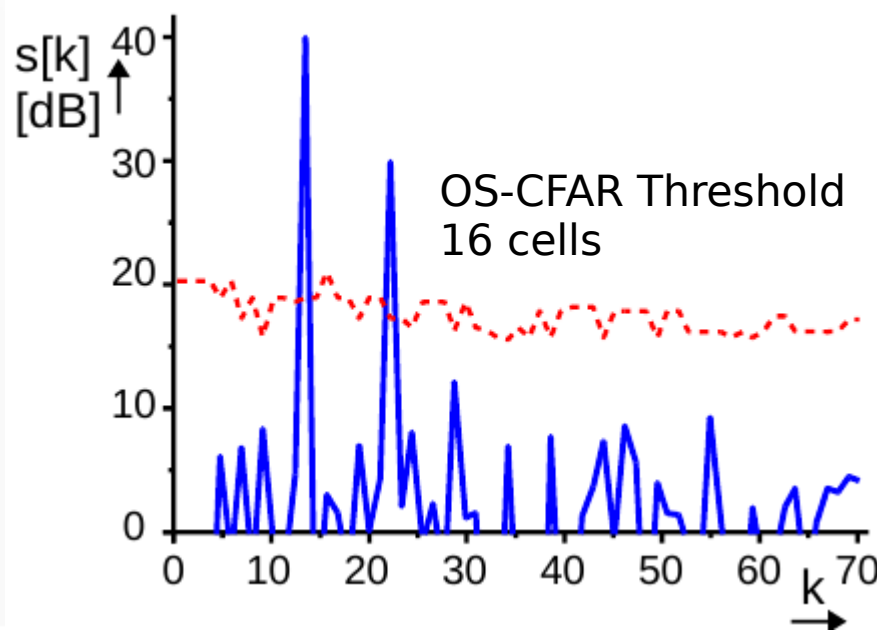
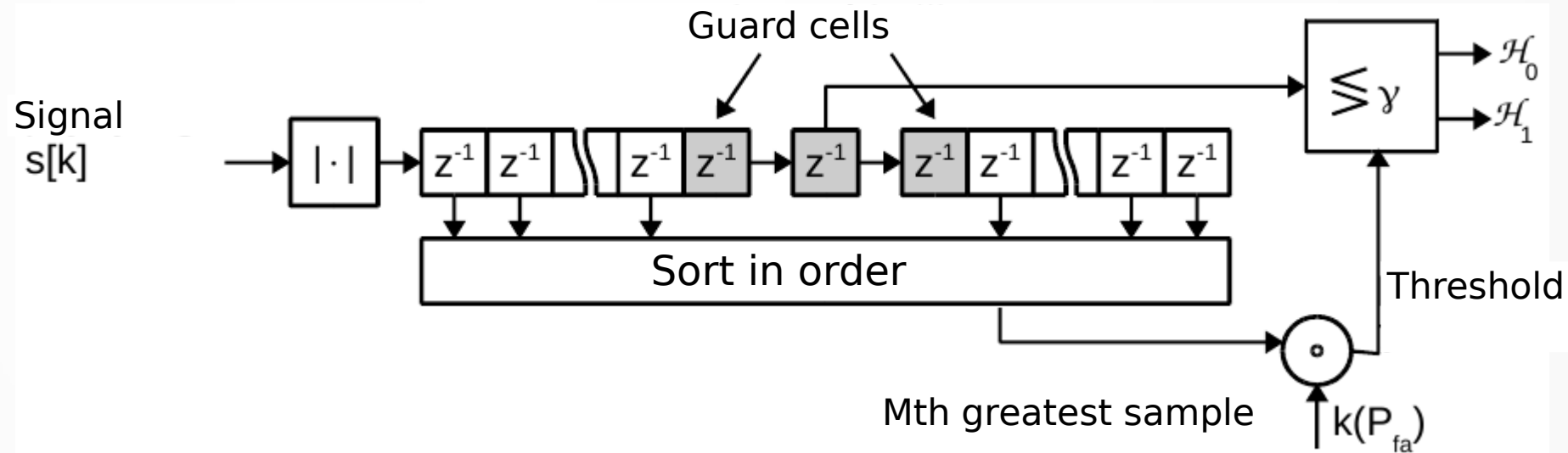
Compute and use noise estimates as in Greatest-of, but remove the largest M samples before computing each average



- Up to M nearby targets can be in each window without affecting threshold – dependent on target statistics
- Ordering the samples from each window is more computationally expensive than plain averaging

Adaptive detection – OS CFAR

- Ordered statistics (OS)
- Better in case of multiple targets or at clutter border
- Lower gain



References

- P. Šedivý – Rádiové systémy, lectures, CTU FEE Prague 2011-2016
- M. O'Donnell – Introduction to Radar Systems, MIT Lincoln Laboratory, set of lectures, 2002
- M. Skolnik – Radar Handbook, McGraw-Hill 2008
- M. Richards – Fundamentals of Radar Signal Processing, McGraw-Hill, New York, 2005

Thank You!