

Secure Chaotic Spread Spectrum Systems

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Outline

- Introduction
- Chaotic SS signals
- Security/LPI performance
 - Intercept receivers
 - Binary correlating detection
 - “Mismatch” problem
 - Particle-filtering based approach
 - Dual-antenna approach
 - Numerical results
- Conclusions



Introduction

- LPI/LPD-Secure/covert communications
- Spread-spectrum systems
 - Direct sequences
 - PN binary sequences
 - Chaotic sequences
 - Frequency hopping
 - Time hopping (UWB)
- Interceptors
 - likelihood-ratio test
 - Energy detector



Chaotic Signals

- Generate chaotic spreading sequences

- Discrete Chaotic Map

- Exponential Map, Triangular Map....

- For Example: logistic map

$$x_{n+1} = \alpha x_n (1 - x_n) \quad 0 \leq x_n \leq 1, 0 \leq \alpha \leq 4$$

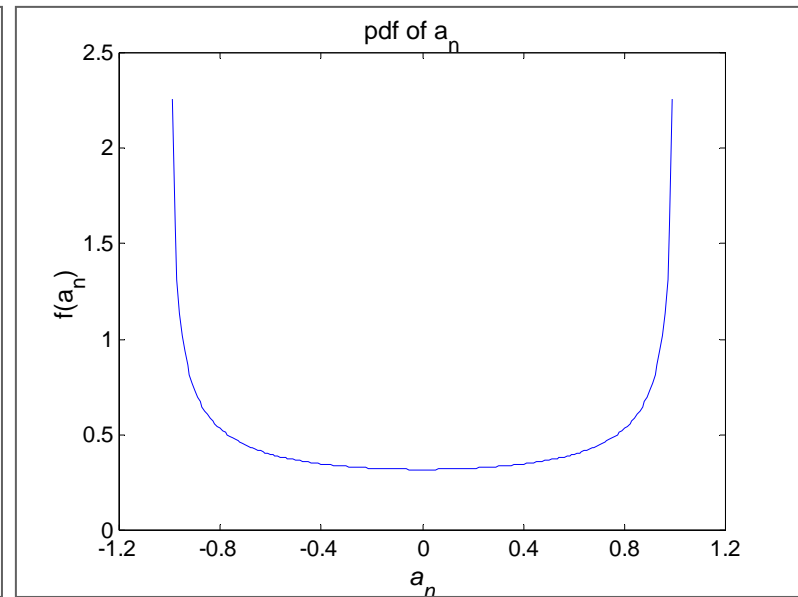
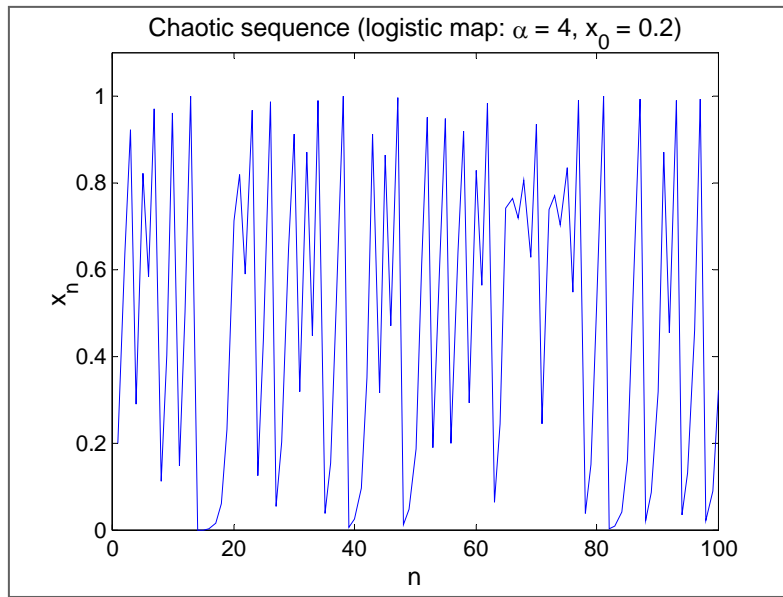
- Bipolar signaling

$$a_n = 2x_n - 1$$

- PDF of $\{a_n\}$

$$f(a_n) = \frac{1}{\pi \sqrt{1 - a_n^2}}, \quad -1 \leq a_n \leq 1$$

Properties of Chaotic Sequences



- Non-binary and non-periodic
- Random-like behaviors
- Good auto- and cross-correlation
- Large number of available spreading sequences for multiple-access applications



System Model

○ Received Signals

$$r(t) = \begin{cases} \sqrt{2P}a(t)\cos(\omega_0 t + \phi) + n(t), & H_1 \\ n(t), & H_0 \end{cases} \quad 0 \leq t \leq T$$

where

$$a(t) = \sum_{n=-\infty}^{\infty} a_n p(t - nT_c - \tau T_c)$$

The chip epoch τT_c is modeled by r.v. τ , uniformly distributed in $[0, 1)$.



Binary Correlating Method

- Likelihood ratio test (Optimum Intercept Receivers)
 - Synchronous coherent
 - Synchronous noncoherent
 - Asynchronous coherent
 - Asynchronous noncoherent
- Gaussian approximation

$$\Lambda(r(t)) = \kappa_1 E_{\varepsilon, \phi} \left\{ \prod_{n=0}^{N-1} \left[\sum_{q=0}^{Q-1} \exp \left(\frac{2\sqrt{2P}}{N_0} \int_{nT_c}^{(n+1)T_c} r_{\varepsilon, \phi}(t) b_q(t) \cos(\omega_0 t) dt \right) \right] \right\}$$

Synchronous Coherent Case

- Using Gaussian approximation, we obtain

$$m_\lambda = N(N_0 T_c)(0.5 + \gamma_c C \delta_{k,1})$$

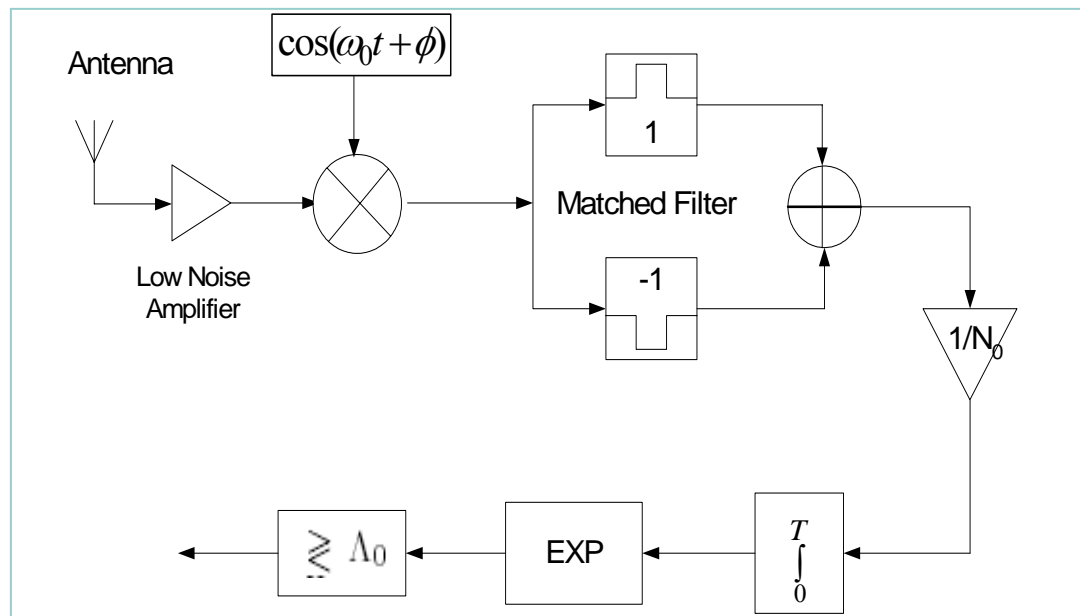
$$\sigma_\lambda^2 = N(N_0 T_c)^2 (0.5 + (2C\gamma_c + D\gamma_c^2) \delta_{k,1})$$

$$P_D = Q\left(\frac{Q^{-1}(P_{FA}) - \sqrt{2N\gamma_c C}}{\sqrt{1 + 4C\gamma_c + 2D\gamma_c^2}}\right)$$

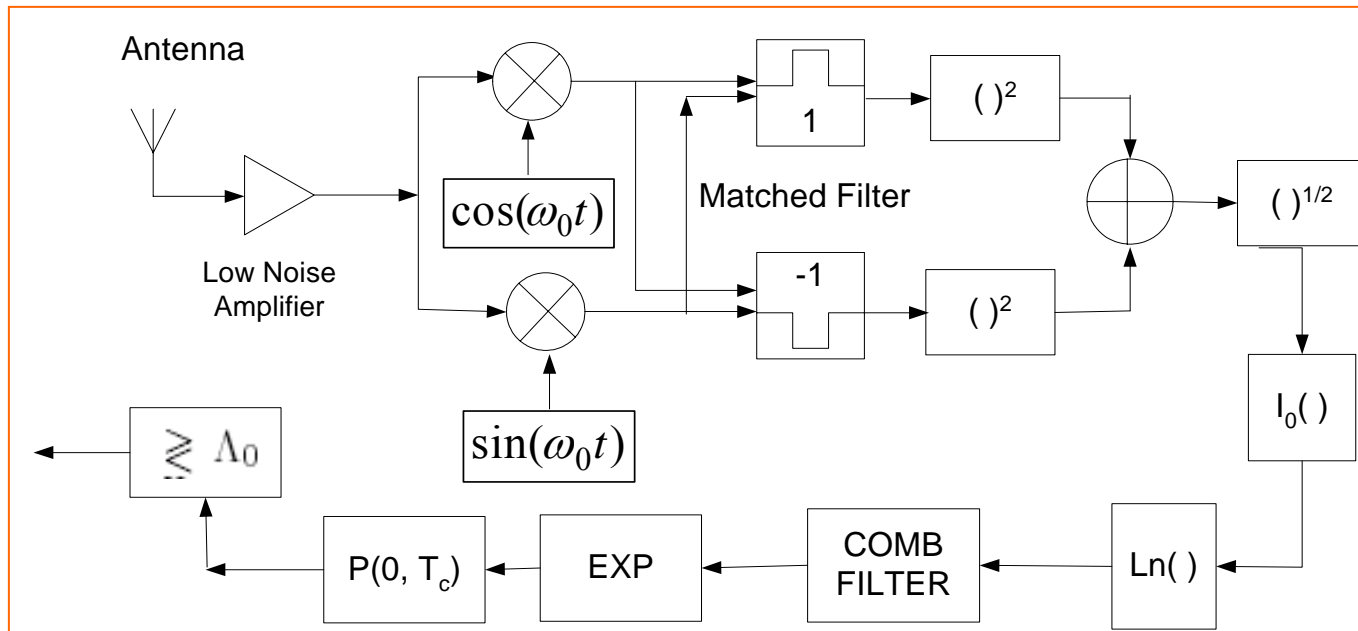
(a) Binary Synchronous Coherent Detector

$$C = \frac{E[a^2]}{E[|a|]}$$

$$D = \frac{\text{Var}(a^2)}{E^2[|a|]}$$



Synchronous Noncoherent Case



The mean and variance of λ is

$$m_\lambda = N(N_0 T_c)(1 + \gamma_c C \delta_{k,1})$$

$$\sigma_\lambda^2 = N(N_0 T_c)^2 (1 + (2C\gamma_c + 0.5D\gamma_c^2) \delta_{k,1})$$

$$\Rightarrow P_D = Q\left(\frac{Q^{-1}(P_{FA}) - \sqrt{N}\gamma_c C}{\sqrt{1 + 2C\gamma_c + 0.5D\gamma_c^2}}\right)$$



Asynchronous Cases

○ Assume chip epoch is $U[0, T_c)$

● Coherent case

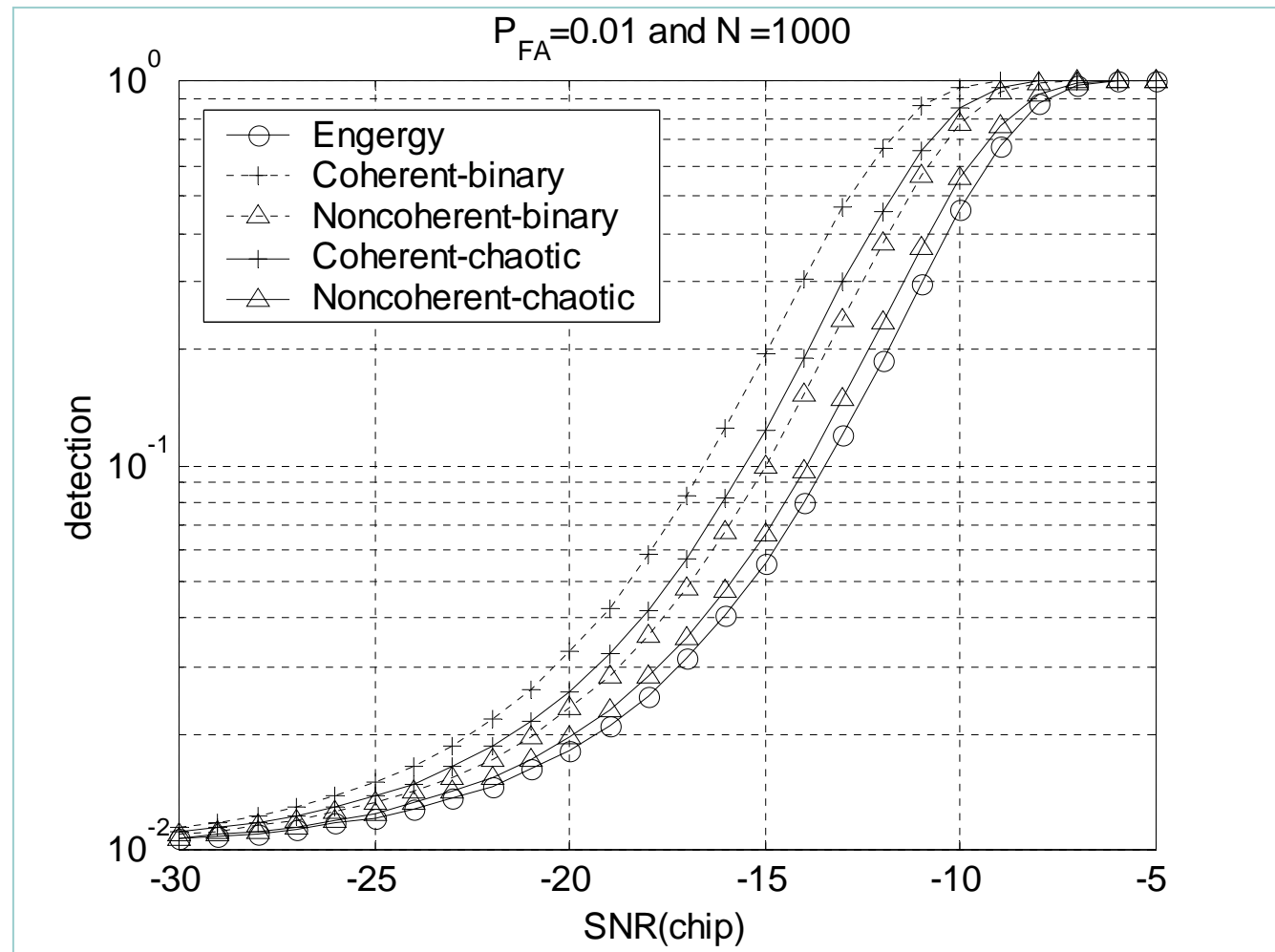
$$P_D(\lambda/\tau) = Q\left(\frac{Q^{-1}(P_{FA}) - \sqrt{2NC}(1-2\tau+2\tau^2)\gamma_c}{\sqrt{1+4C\gamma_c}}\right)$$
$$\Rightarrow \bar{P}_D = \int_0^1 Q\left(\frac{Q^{-1}(P_{FA}) - \sqrt{2NC}(1-2\tau+2\tau^2)\gamma_c}{\sqrt{1+4C\gamma_c}}\right) d\tau$$

● Noncoherent case

$$P_D(\lambda/\tau) = Q\left(\frac{Q^{-1}(P_{FA}) - \sqrt{NC}(1-\tau+\tau^2)\gamma_c}{\sqrt{1+2C\gamma_c}}\right)$$
$$\Rightarrow \bar{P}_D = \int_0^1 Q\left(\frac{Q^{-1}(P_{FA}) - \sqrt{NC}(1-\tau+\tau^2)\gamma_c}{\sqrt{1+2C\gamma_c}}\right) d\tau$$

Performance Comparison

Chaotic vs. Binary PN (Sync)





Particle-Filtering Based Detector

- Uncertainties in Chaotic Signals
 - Amplitude uncertainty (mismatch problems)
 - For all detection scenarios with chaotic signals
 - Phase uncertainty
 - Noncoherent detections
 - Delay uncertainty
 - Asynchronous detections



Particle-Filtering Based Detector

- Design particle sets
 - approximate the unknown random variables
 - select the most likely particle statistically
 - combat the impact due to uncertainties
- Reduce computational complexity
 - Updated particles for each iteration
 - Fixed particles for each iteration

Particle-Filtering Based Detector

- LRT function with particle filtering

$$\Lambda(r(t)) = \frac{p(\mathbf{r}_I | H_1)}{p(\mathbf{r}_I | H_0)} \underset{H_0}{\overset{H_1}{\approx}} \Lambda_0 \quad \leftarrow \text{Coherent detection}$$

$$\Lambda(r(t)) = \frac{\prod_{i=1}^N \left(\sum_{j=1}^{L_a} p(\mathbf{r}_{I,i} | a_i(j)) \right)}{L_a^N \prod_{n=1}^N p(\mathbf{r}_{I,n})}$$

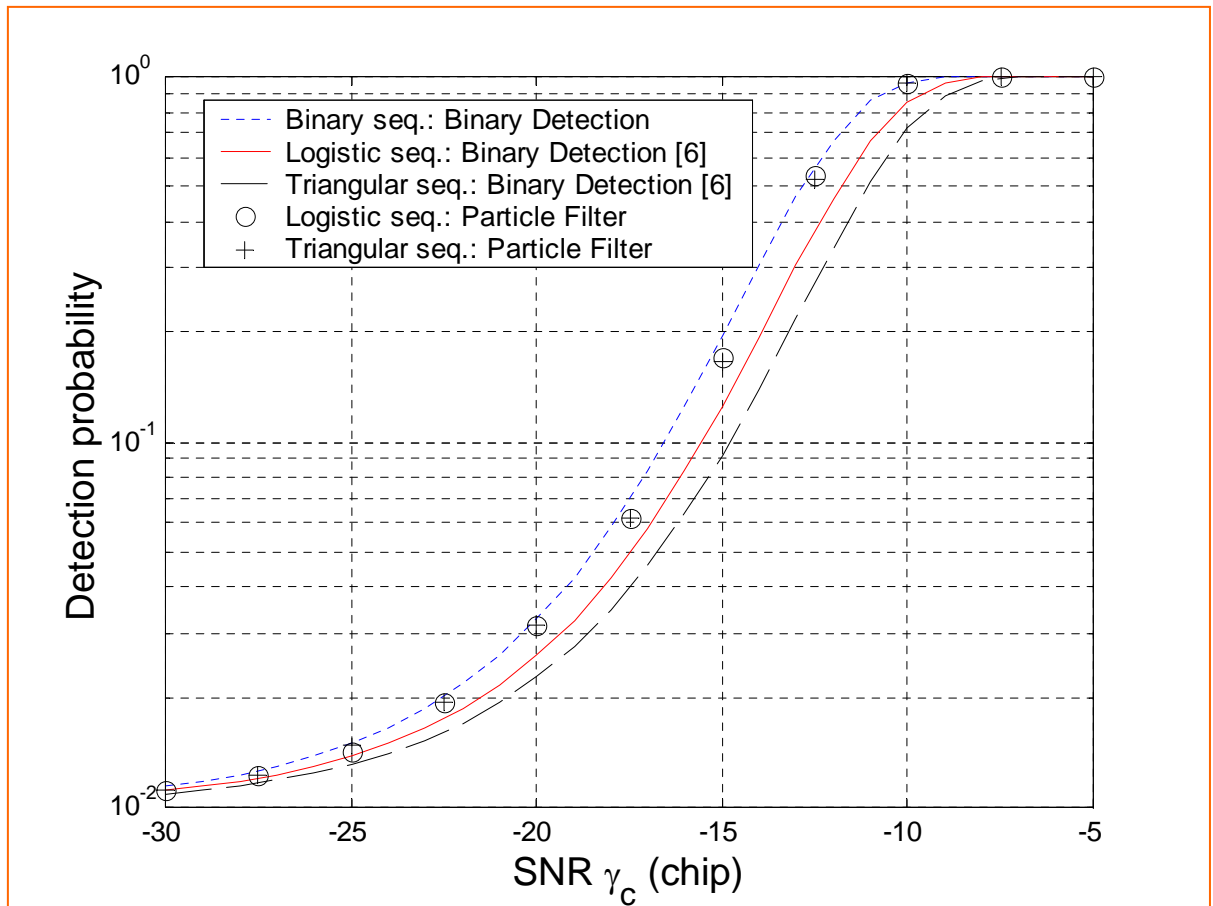
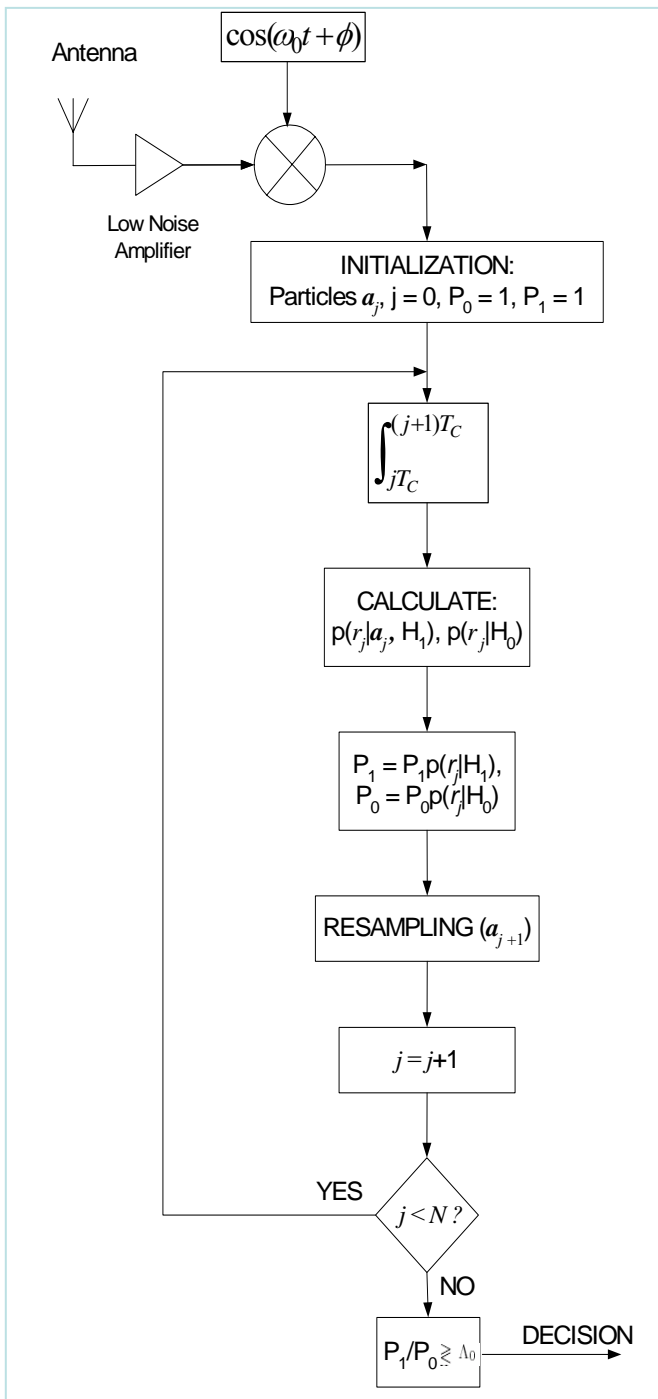
$$\Lambda(r(t)) = \frac{p(\mathbf{r}_I, \mathbf{r}_Q | H_1)}{p(\mathbf{r}_I, \mathbf{r}_Q | H_0)} \underset{H_0}{\overset{H_1}{\approx}} \Lambda_0 \quad \leftarrow \text{Noncoherent detection}$$

$$\Lambda(r(t)) = \frac{\prod_{i=1}^N \left(\sum_{j=1}^{L_a} \sum_{p=1}^{L_p} p(\mathbf{r}_{I,i}, \mathbf{r}_{Q,i} | a_i(j), \phi_i(p)) \right)}{L_a^N L_p^N \prod_{n=1}^N p(\mathbf{r}_{I,n}, \mathbf{r}_{Q,n})}$$

Notice: probability density functions $p(\bullet)$ is used to select **the particles** $a_i(j)$ and $\phi_i(p)$ which are mostly close to the actual amplitude and phase.

Particle-Filtering Based Detector

Synchronous coherent receivers with $P_{FA} = 0.01$, $L_a = 50$, and $N = 1000$



Asynchronous Detection: Multiple sampling

- Obtain multiple observations by multiple sampling at τ_n (combat delay uncertainty)

$$\mathbf{R}_I = \begin{pmatrix} r_{I,1}^1 & r_{I,2}^1 & \cdots & r_{I,N}^1 \\ \vdots & \vdots & \ddots & \vdots \\ r_{I,1}^{N_d} & r_{I,1}^{N_d} & \cdots & r_{I,N}^{N_d} \end{pmatrix} \quad \mathbf{R}_Q = \begin{pmatrix} r_{Q,1}^1 & r_{Q,2}^1 & \cdots & r_{Q,N}^1 \\ \vdots & \vdots & \ddots & \vdots \\ r_{Q,1}^{N_d} & r_{Q,1}^{N_d} & \cdots & r_{Q,N}^{N_d} \end{pmatrix}$$

$$\mathbf{N}_I = \begin{pmatrix} n_{I,1}^1 & n_{I,2}^1 & \cdots & n_{I,N}^1 \\ \vdots & \vdots & \ddots & \vdots \\ n_{I,1}^{N_d} & n_{I,1}^{N_d} & \cdots & n_{I,N}^{N_d} \end{pmatrix} \quad \mathbf{N}_Q = \begin{pmatrix} n_{Q,1}^1 & n_{Q,2}^1 & \cdots & n_{Q,N}^1 \\ \vdots & \vdots & \ddots & \vdots \\ n_{Q,1}^{N_d} & n_{Q,1}^{N_d} & \cdots & n_{Q,N}^{N_d} \end{pmatrix}$$



Parallel Detection Algorithm

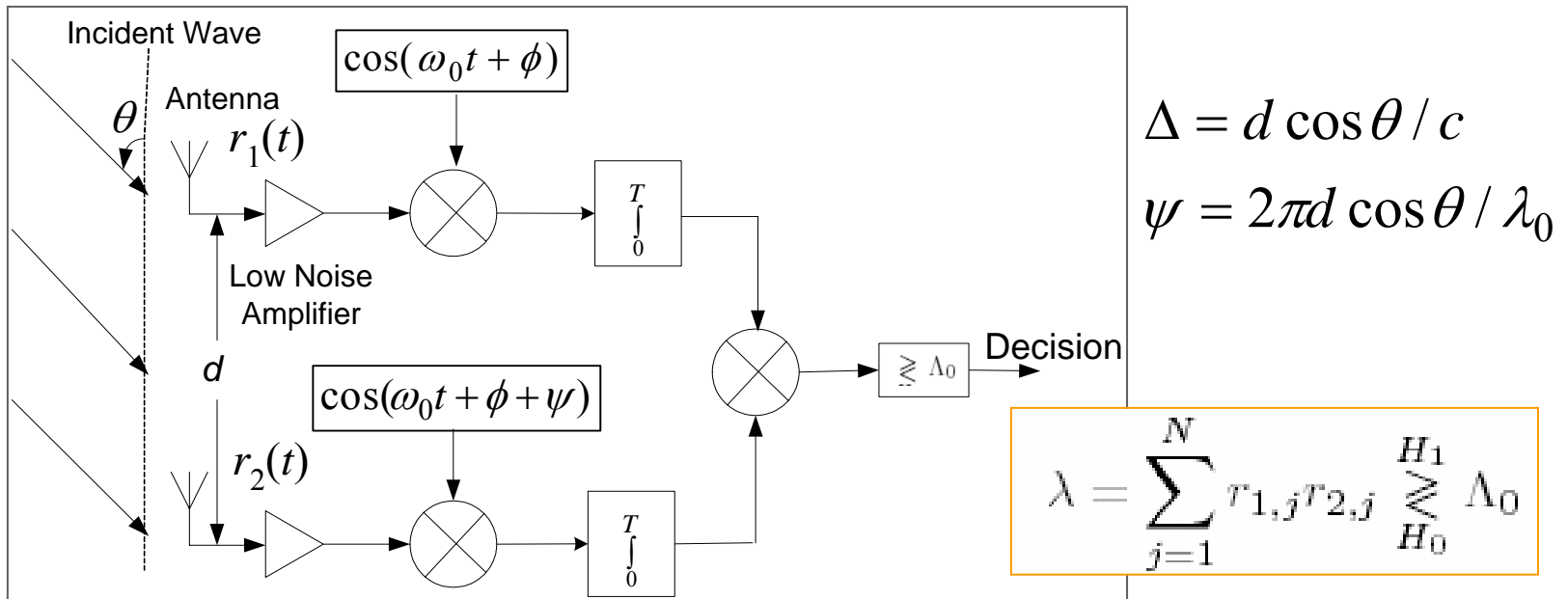
- LRT function

$$\Lambda(r(t)) = \max_n \left\{ \frac{p(\mathbf{r}_I^n | H_1)}{p(\mathbf{r}_I^n | H_0)}, n = 1, 2, \dots, N_d \right\} \underset{H_0}{\overset{H_1}{\gtrless}} \Lambda_0$$

$$\Lambda(r(t)) = \max_n \left\{ \frac{p(\mathbf{r}_I^n, \mathbf{r}_Q^n | H_1)}{p(\mathbf{r}_I^n, \mathbf{r}_Q^n | H_0)}, n = 1, 2, \dots, N_d \right\} \underset{H_0}{\overset{H_1}{\gtrless}} \Lambda_0$$

Notice: The row having the minimum delay is automatically selected by probability density functions $p(\bullet)$ to detect the presence of radio signals.

Dual-Antenna Approach: Synchronous coherent case



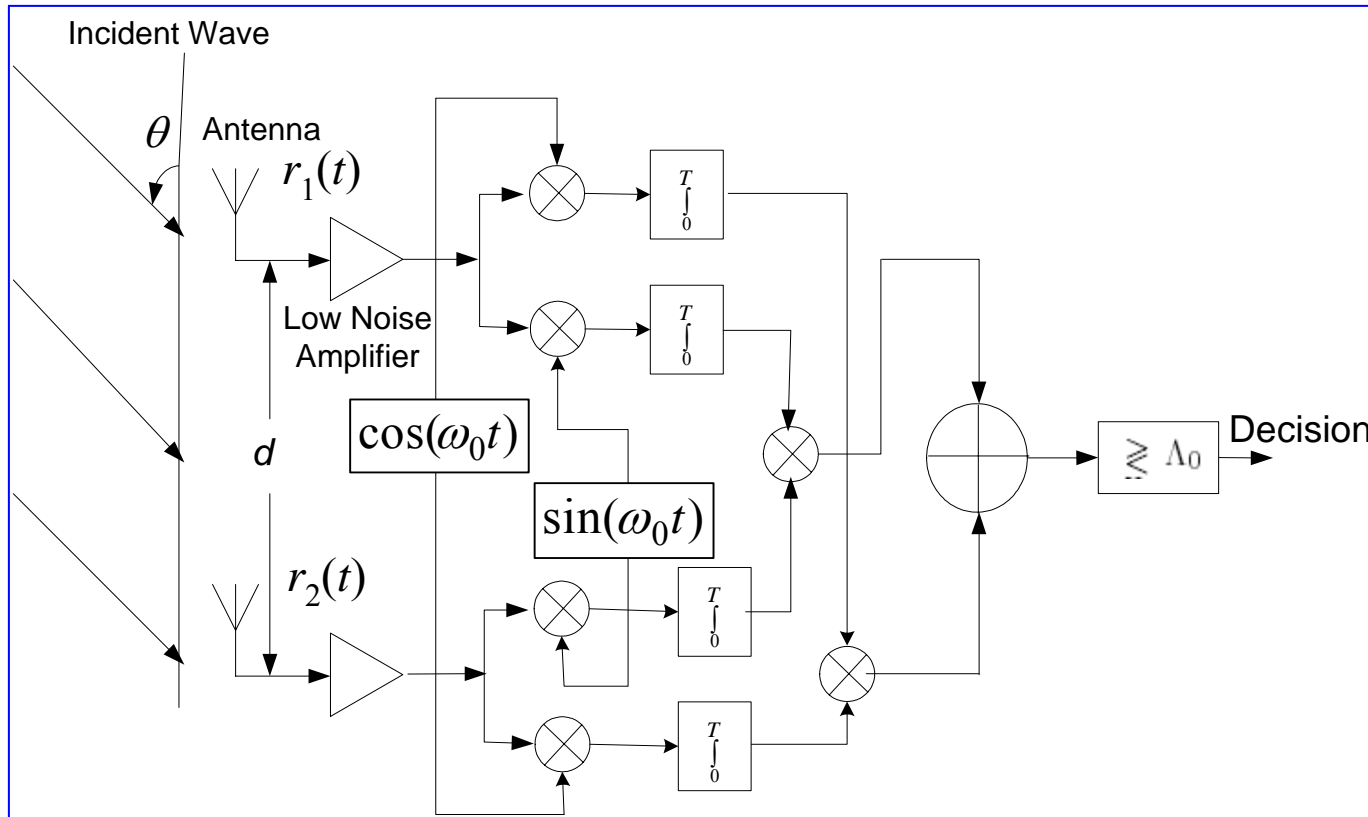
Signal Model

$$\begin{cases} r_1(t) = \sqrt{2P}a(t) \cos(\omega_0 t + \phi) + n_1(t) \\ r_2(t) = \sqrt{2P}a(t) \cos(\omega_0 t + \phi + \psi) + n_2(t) \end{cases}$$

Detection Probability

$$P_D = Q\left(\frac{Q^{-1}(P_{FA}) - 2\sqrt{N}\gamma_c}{\sqrt{1+4\gamma_c}}\right)$$

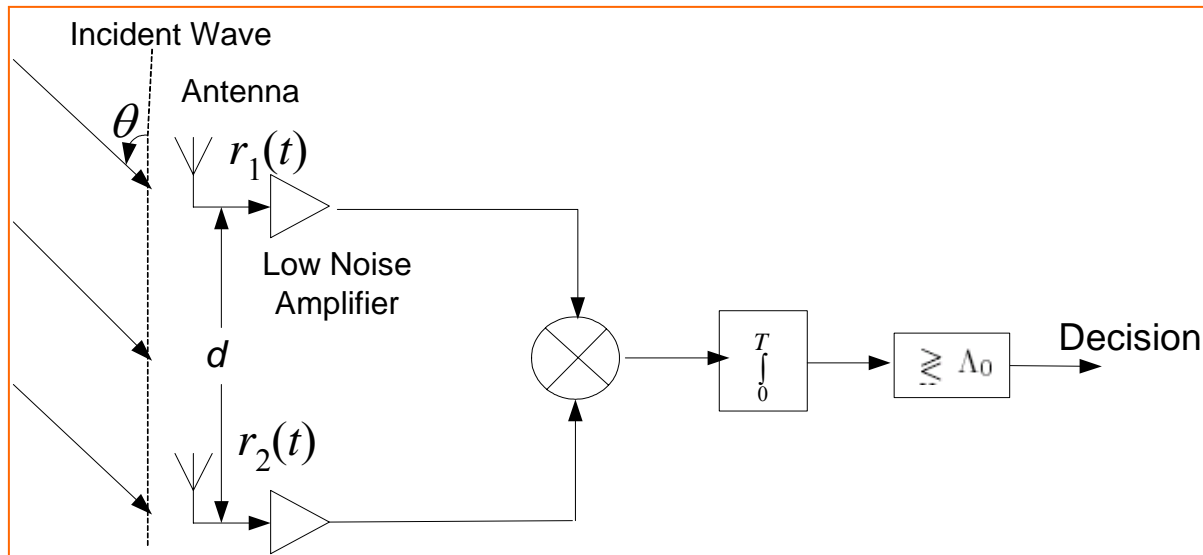
Dual-Antenna Approach: Synchronous noncoherent case



$$\lambda = \sum_{j=1}^N (r_{I,1,j} r_{I,2,j} + r_{Q,1,j} r_{Q,2,j}) \underset{H_0}{\overset{H_1}{\gtrless}} \Lambda_0$$

$$P_{D|\theta} = Q \left(\frac{Q^{-1}(P_{FA}) - \sqrt{2N} \Omega(\theta) \gamma_c}{\sqrt{1 + 2\gamma_c}} \right)$$

Dual-Antenna Approach: Asynchronous case



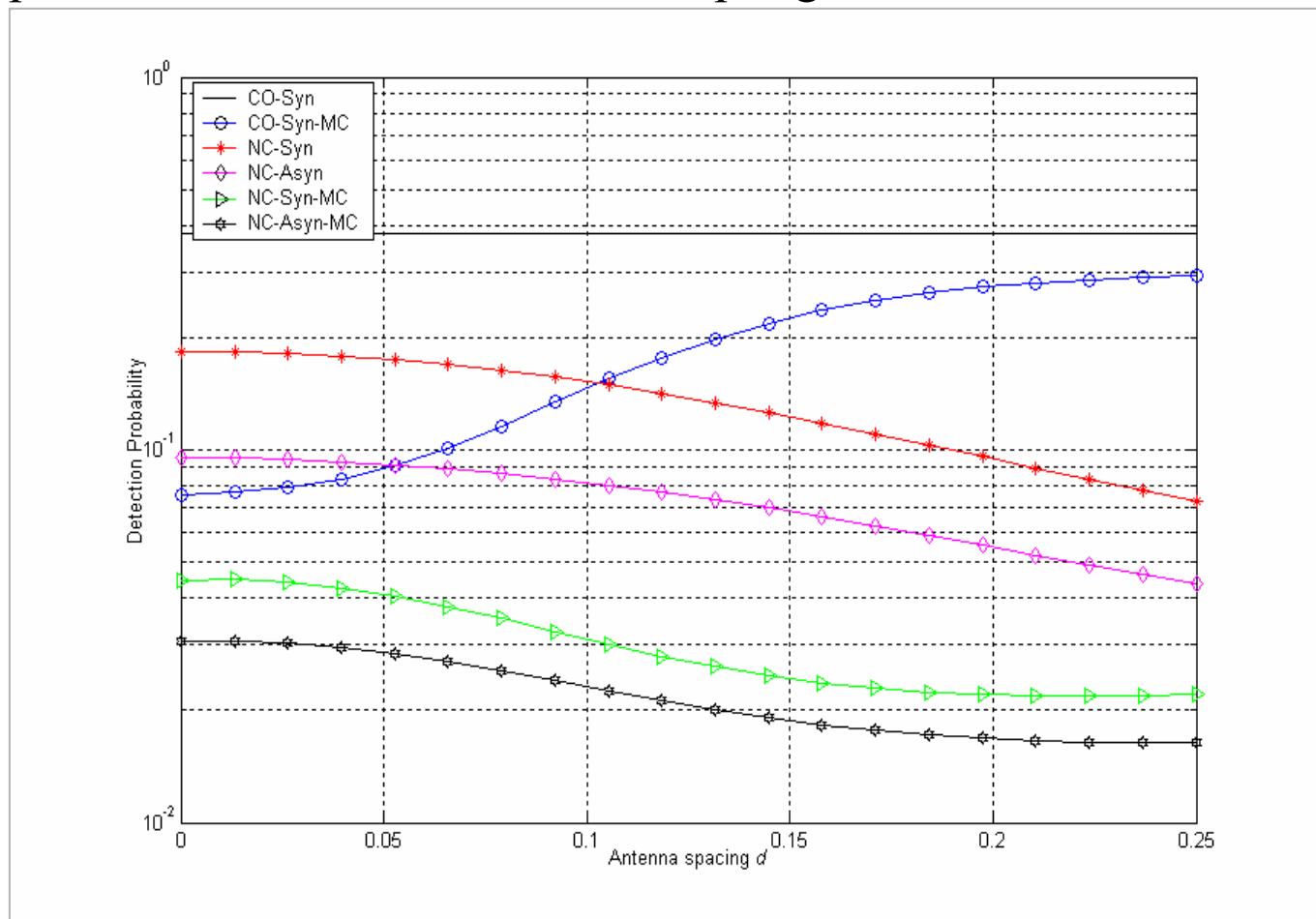
$$\lambda = \int_0^T r_1(t)r_2(t)dt \underset{H_0}{\overset{H_1}{\gtrless}} \Lambda_0$$

$$P_{D|\theta} = Q\left(\frac{Q^{-1}(P_{FA}) - \Omega(\theta)\sqrt{N}\gamma_c}{\sqrt{1+2\gamma_c}}\right)$$

$$\Omega(\theta) = \cos(2\pi d \cos \theta / \lambda_0)$$

Numerical Results

LPI performance of chaotic DS SS signals with various d , $N = 1000$, and chip SNR = -15 dB. MC: Mutual coupling.





Conclusions

- The mismatch between chaotic sequences and binary detection results in the LPI performance improvement;
- Particle-filtering based approach can be used to combat the uncertainties and then improve the detection performance;
- Dual antenna approach can also suppress the uncertainties; however, it is subject to mutual coupling.



Thank You!

Any Questions?