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Zero-crossings Based Nonparametric Goodness-of-Fit Tests for Spectrum Sensing in Cognitive Radios under Noise Uncertainty

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Goodness-of-Fit Tests (GoFT)

- In the classical Neyman-Pearson hypothesis testing, both hypotheses are known
- In GoFT, distribution of the test statistic is known under H₀ and assumed to be unknown under H₁
- Examples : Tests for independence, tests for deviation from a specific distribution under H₀



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GoFT for Spectrum Sensing (SS) in CR

The choice of a GoFT depends on:

- Statistics of noise
- Knowledge of noise variance
- Number of observations
- Signal characteristics of the Primary



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Existing GoFTs in SS context

- Wang et al. [2009] a GoFT based on the Anderson-Darling Statistic (ADD)
- Shen et al. [2011] a modified GoFT based on ADD and called it the Blind Detector (BD)
- Denkovski et al. [2012] a higher order statistic based GoFT
- Rostami et al. [2012] an ordered statistic based GoFT



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This work...

- We propose a new GoFT based on a modification of an existing test using zero-crossings (Kedem et al. 1982)
- Advantages of our detector:
 - Can be applied under Gaussian and Laplacian noise distributions
 - Robust to noise uncertainty
 - Closed form for the optimal threshold



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System Model

- A single CR node carrying out SS with *M* observations.
- Under Gaussian noise, The hypothesis testing problem is

 $\begin{aligned} H_0 : Y_i \sim \mathcal{N}(0, \sigma_n^2) \\ H_1 : Y_i \nsim \mathcal{N}(0, \sigma_n^2) \end{aligned}$

Under Laplacian noise, The hypothesis testing problem is

 $H_0: Y_i \sim \mathcal{L}(\sigma_n^2)$ $H_1: Y_i \nsim \mathcal{L}(\sigma_n^2)$



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Energy Detector (ED)

• When σ_n^2 is known, the ED has the following critical region

$$\left\{Y_{i}, i \in \mathcal{M} : \sum_{i=1}^{M} Y_{i}^{2} > \tau_{\mathsf{ED}}\right\},\tag{1}$$

• When $n_i \sim \mathcal{N}(0, \sigma_n^2)$,

$$\tau_{\rm ED} = \gamma^{-1} \left(1 - \alpha, \frac{M - 1}{2}, \frac{2\sigma_n^2}{M} \right), \tag{2}$$

where $\gamma^{-1}(x, A, B)$ is the normalized inverse gamma CDF evaluated at *x*, with parameters *A* and *B*.

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Anderson Darling Detector (ADD) - 1/2

The Anderson-Darling statistic is defined as

$$A_{c}^{2} \triangleq -\frac{\sum_{i=1}^{M} (2i-1)(\ln Z_{i} + \ln(1-Z_{M+1-i}))}{M} - M \qquad (3)$$

with $Z_i = F_0(Y_i)$, where $F_0(\cdot)$ is the distribution under \mathcal{H}_0 . Also, $Y_1 \leq Y_2 \leq \cdots \leq Y_M$.

The ADD has the following critical region

$$\left\{ Y_{i}, i \in \mathcal{M} : \mathcal{A}_{c}^{2} \geq \tau_{\mathsf{ADD}} \right\},\tag{4}$$



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Anderson Darling Detector (ADD) - 2/2

For any $p_f = \alpha$ and for moderate values of M, τ_{ADD} satisfies

$$1 - \frac{\sqrt{(2\pi)}}{\tau_{ADD}} \sum_{\ell=0}^{\infty} \frac{(-1)^{\ell} \Gamma(0.5+\ell)}{\Gamma(0.5)\ell!} \exp\left(-\frac{\pi^2 (4\ell+1)^2}{8\tau_{ADD}}\right) \times (4\ell+1) \int_0^{\infty} \exp\left(\frac{\tau_{ADD}}{8(w^2+1)} - \frac{\pi^2 w^2 (4\ell+1)^2}{8\tau_{ADD}}\right) dw = \alpha.$$
(5)



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Blind Detector (BD) - 1/2

- When the noise process is i.i.d. Gaussian, the construction of the BD is such that the test statistic is independent of σ_n².
- M observations are divided into n windows of m observations each and the test statistic is constructed as follows. Define

$$X_{l} \triangleq \sum_{u=0}^{m-1} \frac{Y_{ml-u}}{m}, \quad S_{l}^{2} \triangleq \sum_{u=0}^{m-1} \frac{(Y_{ml-u} - X_{l})^{2}}{m-1},$$
 (6)

and
$$B_l \triangleq \frac{X_l}{S_l/\sqrt{m}}, l = 1, \cdots, m.$$

Then, the BD has the following critical region

$$\{Y_i, i \in \mathcal{M} : B_l \geq \tau_{\mathsf{BD}}\}.$$



(7)

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Blind Detector (BD) - 2/2

It is known that when n_i ~ N(0, σ_n²), the statistic B_l is student-t distributed with parameter m − 1. Therefore, for a given p_f level α, τ_{BD} satisfies

$$\frac{1}{2} - \frac{\tau_{\text{BD}} \Gamma\left(\frac{m}{2}\right) \, _2\mathcal{F}_1\left(\frac{1}{2}, \frac{m}{2}; \frac{3}{2}; -\frac{\tau_{\text{BD}}^2}{m-1}\right)}{\sqrt{\pi(m-1)} \Gamma\left(\frac{m-1}{2}\right)} = \alpha, \qquad (9)$$

with $_2\mathcal{F}_1(\cdot;\cdot;\cdot)$ representing the Kummer's hypergeometric function.

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Disadvantages of ED, ADD and BD

- Both ED and ADD requires the knowledge of σ_n^2
- Additionally, calculation of \(\tau_{ADD}\) needs evaluation of an integral over an infinite series
- The analysis of BD fails in non-gaussian noise. Extending the same idea to other distributions is not easy.
- Both ADD and BD are limited to small sample sizes.



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Basics of Zero-crossings (ZC) (1/2)

• Let ∇^k denote the k^{th} order difference operator.

$$\nabla Y_i \triangleq Y_i - Y_{i-1} \tag{10}$$

$$\nabla^2 Y_i = \nabla(\nabla Y_i) = Y_i - 2Y_{i-1} + Y_{i-2}$$
 (11)

$$\nabla^{k} Y_{i} = \sum_{j=0}^{k} {k \choose j} (-1)^{j} Y_{i-j}, \quad i \in \mathcal{M}$$
 (12)

The k^{th} order ZC of $\{Y_i, i \in \mathcal{M}\}$ is defined as the number of ZCs in $\nabla^{k-1} Y_i$. Also called the *Higher Order Crossings* (HOC), they are denoted by $D_{k,M}$.



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Basics of Zero-crossings (ZC) (2/2)

• Let $\Delta_{j,M}$, and $\mu_{j,M}$ be defined as

$$\Delta_{j,M} \triangleq \begin{cases} D_{1,M}, & j = 1, \\ D_{j,M} - D_{j-1,M}, & j = 2, \cdots, k-1 \\ (M-1) - D_{k-1,M}, & j = M, \end{cases}$$
(13)

and
$$\mu_{j,M} \triangleq \mathbb{E}\Delta_{j,M}, j = 1, \cdots, k,$$
 (14)

where $\mathbb{E}(\cdot)$ denotes the expectation operator. Observe that $\sum_{j=1}^{k} \Delta_{j,M} = M - 1$.

Under Gaussian noise, it can be shown that

$$\mathbb{E}D_{k,M} = (M-1)\left\{\frac{1}{2} + \frac{1}{\pi}\sin^{-1}\left(\frac{k-1}{k}\right)\right\},$$



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The Ψ^2 statistic and the Ψ SD

• The goodness-of-fit measure Ψ_M^2 upto a given order k is defined as

$$\Psi_M^2 \triangleq \sum_{j=1}^k \frac{(\Delta_{j,M} - \mu_{j,M})^2}{\mu_{j,M}}.$$
 (16)

- Under Gaussian noise and for moderately large *M*, $\Psi_M^2 \sim \chi_3^2(11)$, very closely
- The ΨSD has a critical region

$$\left\{ Y_{i}, i \in \mathcal{M} : \Psi_{M}^{2} > \tau_{\Psi \text{SD}} \right\},$$
(17)

(18)

where for a given p_f level α , $\tau_{\Psi SD}$ satisfies

$$Q_{\frac{3}{2}}(\sqrt{11},\sqrt{\tau_{\Psi \text{SD}}}) = \alpha,$$

with $Q_M(\cdot, \cdot)$ representing the Marcum-Q function of order M

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The m Ψ^2	statistic and	l the mΨ	SD (1/2)				
 It was observed through simulations that under some cases, only first few ZCs were different under H₀ and H₁ The modified Ψ² statistic is defined as 							
	$_{m}\Psi_{M}^{2}\triangleq brace$	$\sum_{j=1}^{k} e^{-(j-1)} \frac{(\lambda_{j})}{k}$	$\frac{(\Delta_{j,M}-\mu_{j,M})^2}{\mu_{j,M}}$	(19)			

The mΨSD has a critical region

$$\left\{Y_{i}, i \in \mathcal{M}: {}_{\mathsf{m}}\Psi_{M}^{2} > \tau_{\mathsf{m}}\Psi_{\mathsf{SD}}\right\},$$
(20)

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The m Ψ^2 statistic and the m Ψ SD (2/2)								

 Under previously stated conditions, we have observed that mΨ²_M statistic follows an F-distribution with parameters 17.5 and 7 respectively. Therefore, τ_{mΨSD} satisfies

$$1 - \mathcal{I}_{\left(\frac{17.5\tau_{m\Psi SD}}{17.5\tau_{m\Psi SD} + 7}\right)} (8.75, 3.5) = \alpha,$$
(21)

with $\mathcal{I}_x(a, b)$ representing the regularized incomplete beta function with parameters *x*, *a* and *b* respectively.





Figure: Detection performance with SNR for known signal case, under Rayleigh fading and Gaussian noise. $M = 32, \alpha = 0.05$.





Figure: Detection performance with SNR for known signal case, under Rayleigh fading and Laplacian noise. $M = 32, \alpha = 0.05$.





Figure: Detection of 4kHz sinusoidal signal, under Rayleigh fading and Gaussian noise. M = 32, $\alpha = 0.05$.





Figure: Detection of 4kHz sinusoidal signal, under Rayleigh fading and Laplacian noise. $M = 32, \alpha = 0.05$.







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- Proposed a modified GoFT based on ZCs, which is robust under noise uncertainty
- It can be readily used under Gaussian and Laplacian noise environments

