Optimal Entropy-based Spectrum Sensing for Cognitive Radio Networks under Severe Path Loss Conditions

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***Abstract*—Recently maritime cognitive radio network is proposed to provide high bandwidth and low communication cost for maritime users. Spectrum sensing is one of the key issues to develop cognitive radio networks. Radio propagation is one of the main differences between maritime and land environment. Traditional detectors such as matched filter, energy detector and cyclostationary detector are not robust under low signal-to-noise ratio and at high sea state conditions. To deal with maritime environmental challenges, an entropy-based spectrum sensing scheme with the optimal number of samples is presented in this paper. Since spectrum sensing is sensitive to the number of samples, the optimal number of samples has been introduced in the proposed scheme to get minimum sensing time and maximum detection probability. Results reveal that existing scheme works well for the lower sea states but failed to perform at higher sea states. Moreover, simulation results show that the entropy-based scheme is robust at higher sea states in comparison with the traditional energy detector.**

***Index Terms*—Cognitive radio network, Maritime communication, spectrum sensing, cooperative detection.**

I. Introduction

NOWADAYS communication systems based on narrow band ultra high frequency band (UHF, $300MHz$-$3GHz$) and very high frequency band (VHF, $30-300MHz$) are used for close water port's ship-to-shore communication. The satellite communication is used for long range ship-to-shore and ship-to-ship communication [1]. Using satellite links for voice calls and internet access to and from the ship is very expensive when compared to land communication. An improvement in existing techniques and new research is needed in order to reduce the cost of communication and provide high speed data rates at sea.

Recently, some new communication systems, particularly for maritime networks, have been proposed. In Singapore, WISE-PORT (WIreless-broadband-access for SEaPORT) provides IEEE 802.16e-based wireless broadband access up to $5Mbps$, with a coverage distance of $15km$, which still requires enhancement [2]. The first digital VHF network with a data rate of 21 and $133kbps$ with a coverage range of $130km$ was developed in Norway [3]. This system operates in the licensed VHF channel which results in narrow bandwidth and slow communication speed. To provide high speed and low cost ship-to-shore and ship-to-ship communication, the mesh/ad hoc network based on IEEE 802.16d mesh technology was proposed in a project called TRITON [4]. The authors developed a prototype that operates at 2.3 and $5.8GHz$.

Using dedicated spectrum in maritime networks is difficult due to congested bandwidth allocation [5]. The network devices on the shore may need to coexist with other radio devices installed on the land. Moreover, it is also required to synchronize the frequency bands around the world as ships may travel between countries and continents. Spectrum issues in maritime networks can be alleviated by incorporating cognitive radio (CR) technology [5]. Moreover, Zhou et al. analyzed data and concluded that much of the spectrum is underutilized at the sea. CR is a key technology that can help to mitigate the scarcity of spectrum by using licensed spectrum bands opportunistically for unlicensed users. CR's advantages associated with opportunistic access of unused licensed band are alleviation of spectrum scarcity, large bandwidth, long range communication using TV band, and reduced cost for communication. The most essential task of CR is the detection of the licensed/primary user (PU), which is achieved by sensing radio environment. This process is called spectrum sensing. If the PU is absent, its spectrum is available for a cognitive radio/secondary user (SU) and is called spectrum hole/white space.

In this paper, the entropy based detection is investigated to counteract the sea state effects. Optimal number of samples are used to calculate the entropy of sensed signal as the information measure of the received PU signal for test statistic. To the best of the author's knowledge, no one has yet considered spectrum sensing in maritime CR networks.

The rest of the paper is organized as follows. Related work is discussed in Section II. In Section III, a brief overview of maritime cognitive radio network and channel modeling is presented. Section IV presents a system model, optimization problem of number of samples in entropy based detection scheme and centralized cooperative spectrum sensing are discussed briefly. Section V demonstrates simulation results

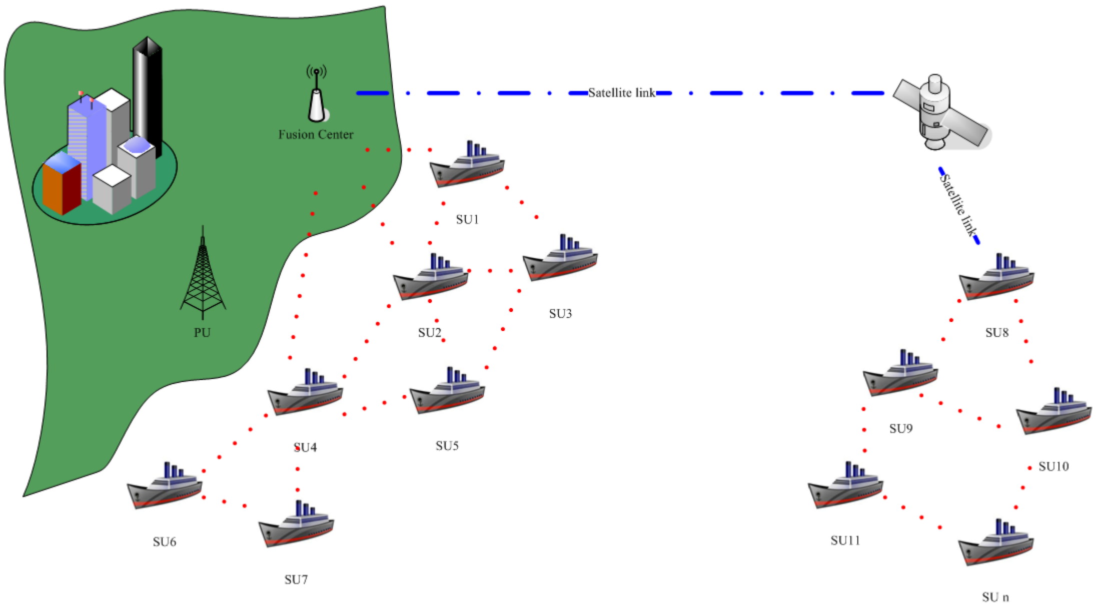

Fig. 1. Architecture of maritime cognitive radio network.

and finally, conclusions are drawn in Section VI.

II. Related Work

Currently, the main focus of research in spectrum sensing for cognitive radio is divided into two main streams: improving local sensing and enhancing cooperative spectrum sensing for better data fusion results. Major local sensing techniques considered for cognitive radios are energy detection, matched filter detection, and cyclostationary detection. Energy detection is the simplest technique that has short sensing time, but its performance is comparatively poor under low SNR conditions. Matched filter detection is another simple technique but it requires prior knowledge about the waveform of the PU. Cyclostationary detection provides reliable spectrum sensing, but it is computationally complex and requires long sensing time [6]. In cooperative spectrum sensing, all the local sensing observations made by SUs are reported to a fusion center and a final decision about the presence or absence of the PU is conducted at the fusion center [7]. Based on the final decision received by the fusion center, each SU reconfigures its operating parameters. Spectrum sensing must produce high probability of detection and low probability of false alarm to achieve better network performance.

Researchers investigated entropy-based detectors to counter the effect of noise uncertainty. In [8] Shannon entropy is calculated as information measure of the received PU signal for test statistics. It is shown that the entropy is independent of noise power under fixed dimension probability space. Therefore, the entropy based detection is robust to noise uncertainties. Spectrum sensing based on the entropy estimation of the cyclostationary features of the received PU is proposed in [9]. In [10] a spectral entropy based PU detection scheme is proposed. All the existing entropy based detectors did well under low SNR conditions but none of them considered sea-state distribution.

The spectrum sensing requirements for maritime cognitive radio networks have to face unique challenges of sea environment because of the following reasons: 1) radio wave propagation over water, 2) surface reflection, and 3) wave occlusions. Therefore, to achieve higher detection probability, CR may need longer sensing time or some advances in the existing spectrum sensing schemes. TV, cellular, and maritime spectrum is available for maritime CR networks and they should be intelligent enough to switch their operating parameters to suit sea state, geographic location/region, and communication range in order to achieve better throughput and quality of service (QoS). UHF is used in the USA for maritime navigation services and therefore it is important to protect the primary band. To achieve this, high probability of detection and low probability of false alarm are required to detect the PU precisely and for efficient utilization of bandwidth, respectively.

III. Maritime Cognitive Radio Network and Channel Modeling

Maritime CR networks can be divided into two types. The first type is the ship-to-ship/ship-to-shore network (close to shore) and the second is the ship-to-ship ad hoc network in deep sea with the support of a satellite communication link as shown in Fig. 1. Each ship is equipped with the devices that are able to perform cognitive radio functions. It regularly senses the radio environment to access the spectrum which is not used by the PU. In networks where ships are far from the land, it becomes impossible to access the fusion center by using industrial, scientific and medical (ISM) band on the land. Therefore, satellite links can be used as an alternate access to the fusion center. In addition to terrestrial CR network's spectrum usage, a ship can switch its operating parameters according to the sea state, geographic location, and density of nodes.

Recently, spectrum measurements in white spaces have been carried out for CR networks on the land. Most common of those are on the television (TV) and cellular bands. On the contrary, investigations are required for spectrum allocated for maritime communications because of the environmental differences. Environmental differences include the obvious maritime radio atmosphere, i.e., sea motion and antenna model. There is almost no obstacle in the sea and the sea surface is also flat, which causes huge path loss due to negative interference between the line of sight (LoS) path and the reflected path [1].

A. Sea Motion

A fundamental of propagation analysis for maritime CR networks is the generation of random sea surface. Sea movement is described by the sea state divided into 10 levels characterized by Pierson-Moskowitz [11]. Sea states $0-3$ are generally considered as calm sea conditions. Moderate sea conditions are in sea states $4-5$. The sea states 6 and above are the worst sea conditions having high waves which cause severe degradation in the communication by affecting the movement of antenna.

B. Channel Model

Unusual challenges arise for maritime wireless networks due to variable channel statistics. The sea surface works as a reflector for the radio propagation and as a result the signal degrades completely along the path. In a terrestrial environment, there are obstacles of different sizes which result in reflection, refraction and scattering of signal in the communication channel. The path loss in terrestrial environment is higher than in free space and defined in [12] as

$$L_T(d) = L_s(d_o) + 10\ \alpha\ log(d/d_o) + X_f \tag{1}$$

where d_o is the distance of a reference location from transmitter with measured path loss $L_s(d_o)$, d is the physical distance between transmitter and receiver, α is the path loss exponent for the radio environment and the Gaussian random contributor X_f with zero mean and standard deviation σ, which represents fast fading effects. The accurate estimation of the path loss exponent is the major characterization of the communication channel. Usually, values of the path loss exponent range from 1 to 4 depending on the physical terrain features.

The path loss in maritime environment increases with the sea state and it increases rapidly in the sea state 5 and above. Path loss in the maritime communication channel during shadowing is proposed in [13] as

$$\begin{aligned} PL(h,f) = PL(d_o) + 10 \times [(0.498 log_{10}(f) \\ +0.793) \times h + 2] \times log_{10}(d/d_o) + X_f \end{aligned} \tag{2}$$

where f is the frequency in GHz, the observable sea height is h in meters, d is the physical distance between transmitter and receiver in meters, $PL(d_o)$ is the path loss simulated at 1 m, and the random variable X_f with zero mean and standard deviation σ which is also represented as a function of wave height:

$$\sigma_f = [0.157f + 0.405] * h. \tag{3}$$

IV. Spectrum Sensing in Maritime Cognitive Radio Networks

A. System Model

In this paper, the UHF band is assumed as the PU's band. It is broad and can offer bandwidth of more than $100MHz$ opportunistically in maritime networks [5]. The communication range for these frequencies is up to $10km$. Ships satisfy all the requirements for acting as the SU which includes spectrum sensing capability and reconfiguration of operating parameters. The base station at the shore acts as the fusion center. The system model for the performance analysis is shown in Fig. 1 in which the maritime wireless network with n SUs is considered.

The ultimate goal of spectrum sensing is to determine the presence of a PU using a binary hypothesis model, i.e., the basic model for spectrum sensing by the SU, which is defined as

$$r(t) = \begin{cases} w(t) & \text{in case of } H_0, \\ s(t) + w(t) & \text{in case of } H_1 \end{cases} \tag{4}$$

where $r(t)$ is the signal received by the SU, $s(t)$ is the transmitted signal of the PU, $w(t)$ is the additive white Gaussian noise (AWGN), H_0 indicates only noise, and the presence of a PU is H_1.

B. Entropy based spectrum sensing with optimum number of samples

Entropy is dependent on the signal power and is highly susceptible to noise uncertainty in time domain. Therefore, the entropy is calculated in frequency domain. For this reason discrete Fourier transform (DFT) is applied on the received signal $r(t)$, we obtain

$$\overline{R(k)} = \begin{cases} \overline{W(k)} & \text{in case of } H_0, \\ \overline{S(k)} + \overline{W(k)} & \text{in case of } H_1 \end{cases} \tag{5}$$

where $k = 0, 1, ...N$ and N is the size of DFT. $\overline{R(k)}$, $\overline{S(k)}$ and $\overline{W(k)}$ denote the complex spectrum of $r(t)$ of (5), $s(t)$ and $w(t)$, respectively. The spectrum magnitude of the measured signal can be represented by the random variable Y for which estimation of probability density function (PDF) is required. Therefore, entropy based frequency modelâs detection strategy can be expressed as

$$H_{L0}(Y)\ vs.\ H_{L1}(Y) \tag{6}$$

where $H_{L0}(Y)$ and $H_{L0}(Y)$ denotes the entropy with number of states L in hypothesis H_0 and H_1, respectively.

For simplicity, the histogram method is used to estimate the probability of each state. The number of states of random variable Y is equal to the number of bins L. Let k_l be the total number of occurrences of l^{th} bin. Then $N = \sum_{l=1}^{L} k_l$ where N is the number of samples. The frequency of occurrences of l^{th} bin is represented as probability p_l, i.e., $p_l = k_l/N$.

The bin width $\Delta = Y_m/L$ where Y_m denotes the maximum spectrum amplitude of the signal [8].

Then, the entropy can be written as

$$E(Y) = -\sum_{l=1}^{L} p_l \; log p_l. \tag{7}$$

After the entropy is calculated for the receiver signal is calculated, we employ the threshold decision rule:

$$D = \begin{cases} E(Y) > \lambda_E & \text{in case of } H_0, \\ E(Y) \leq \lambda_E & \text{in case of } H_1 \end{cases} \tag{8}$$

where λ_E is the threshold. That the calculated entropy is greater than the threshold value implies the absence of PU and vice versa.

It is obvious that the detection probability is increased with the increase in the number of samples in entropy-based local sensing. It is shown in [8] that the entropy detector which needs 10000 samples to achieve the same detection probability while energy detection needs 18000 samples. It is important to find the optimal number of samples for the sea environment to achieve better detection probability. Therefore, one of the optimization problems can be formulated as:

$$\begin{aligned} Find &: N^* \\ Minimize &: \tau_s \\ Subject\ to &: P_d \geq \alpha_L \\ & P_f \leq \beta_L \end{aligned} \tag{9}$$

where N^* is the optimal number of samples for entropy-based detection, τ_s is the sensing time, α_L and β_L are the corresponding local target probability of detection and false alarm, respectively.

A penalty function technique [14] is useful to solve constrained optimization problem given in (9). The penalty function is formulated for the constrained optimization problem given in (9), and then a simplex search method, which is an unconstrained algorithm, is applied. The penalty method applied to (9) can be described as follows:

minimize $\theta_1(N)$

where

$$\begin{aligned} \theta_1(N) = \tau_s(\theta_1(N)) &+ c_1(\alpha_L - P_d)^2 \\ &+ c_2(\beta_L - P_f)^2 \end{aligned} \tag{10}$$

in which $\theta_1(N)$ indicates the new objective function to be optimized. c_1 and c_2 are the penalty parameters and should be greater than zero.

V. Simulation Results

The simulation has been carried out to investigate the performance of spectrum sensing in maritime cognitive radio network. The simulation consists of the sea wave movement model and path loss model as discussed in Section III. It is assumed that SUs are experiencing additive white Gaussian noise (AWGN) with the same variance and the path loss depends on the radio environment during communication. Each SU uses the entropy-based detection scheme with the optimal number N^* and energy detector for its local observation having an average SNR $\overline{\gamma}$. Let SUs be unaware of relevant PU information such as the position, moving direction and velocity.

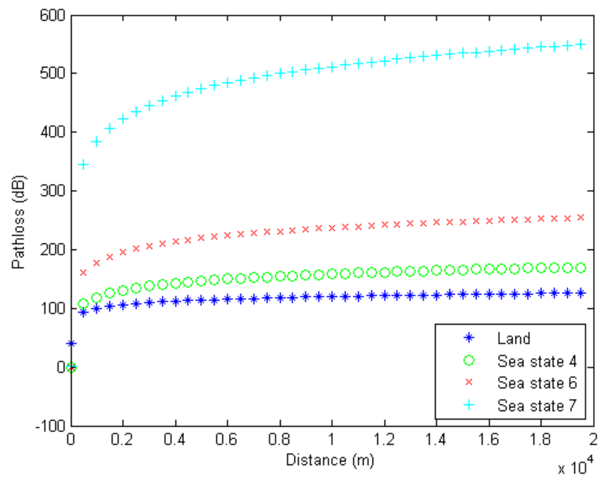

Fig. 2. Comparison of path loss model in land and different sea states.

Fig. 2 shows the path loss for 2.492GHz for different radio environments including land and sea environments. Sea states considered to measure path loss are 4.0, 6.0, and 7.0 having wave heights 2, 4, and $11m$ above sea surface, respectively. The physical distance between the transmitter and the receiver varies from 0 to $20km$ and its reference distance is $1m$. Results show that path loss in the maritime environment is comparable to one in the land environment up to the sea state 4.0. Severe path loss is observed at the sea states higher than 4.0. Path loss almost gets double at sea state 6.0 in comparison with sea state 4.0. For the sea state 7.0, path loss is almost 5 times when compared with either sea state 4.0 or land environment. It becomes worse at higher sea states.

The probability of detection using energy detection and optimal entropy-based detection with the same number of samples was investigated to determine its sensitivity for detecting a PU's presence for a range of SNR from $-10dB$ to $20dB$. According to the draft IEEE 802.22 standard [15], the probability of false alarm should be less than or equal to 0.1. Therefore, the decision threshold λ_E was set to maintain $P_f = 10^{-1}$. Fig. 3 (a) and (b) show that the probability of detection at the land and sea state 4.0 is similar to each other because both of them suffer almost the same path loss. In Fig. 3 (c), when the sea state is 6.0, the probability of detection in case of entropy- based detector is a little higher than energy detection even under low SNR conditions. However, for the sea state 7.0, the probability of detection is near to zero over the entire range of SNR in case of energy detector because of severe path loss but the entropy-based detector can still detect PU signal under good SNR conditions as shown in Fig. 3 (d).

The practical interest in maritime cognitive radio network is to determine the relationship between P_m or P_d and

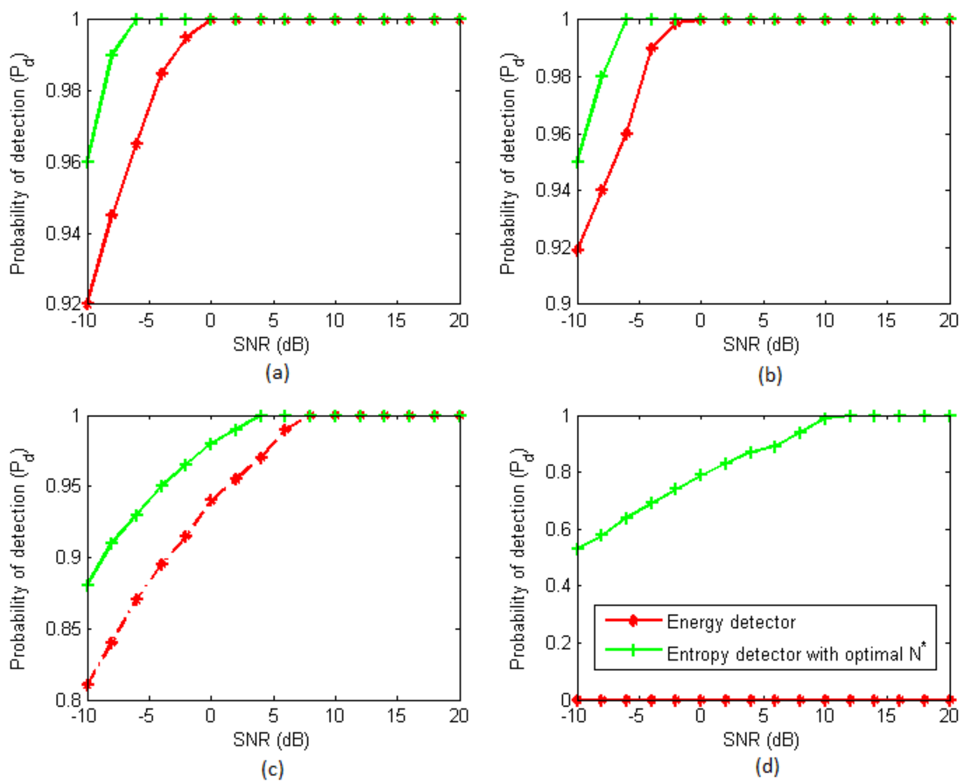

Fig. 3. The impact of SNR on the probability of detection(a) Land Network, (b) Sea state 4, (c) Sea state 6 and (d) Sea state 7.

P_f. Complementary receiver operation characteristic (ROC) curves plot P_f against P_d for a given average SNR and the time bandwidth product TW with varying thresholds. The complementary ROC curves at the land, sea state 4.0, sea state 6.0, and sea state 7.0, when using the energy detector and entropy-based detector with the optimal number of samples N^* as local detectors, are shown in Fig. 4. In this scenario, it is assumed that the average SNR of SU is -5 dB. The result shows that the complementary ROC performance of the entropy-based detector with optimal N is better than that of energy detector in above-mentioned four cases. However, for sea state 6.0 and higher, it cannot detect the primary user with high probability under low P_f.

VI. Conclusion

In this paper, the optimal number of samples for entropy-based detection for maritime cognitive radio network has been calculated. Simulation results show that the performance of energy detector and entropy-based detector is almost same for land environment. However, for the sea states 4, 6 and 7, the entropy-based detector with the optimal number of samples N^* performs better than the energy detector. For sea state 7 and higher, although the entropy-based detector can detect PUs with high probability in comparison with energy detector but still constraints of the probability of detection and false alarm are not satisfied.

One way to improve the sensing performance at higher sea states is to design a new advanced signal processing algorithm in order to detect a distorted signal. An advanced algorithm like cyclostationary feature detection needs a relatively long time for sensing in comparison with the energy detector and entropy-based detector. Therefore, for the future work, adaptive spectrum sensing can be studied, in which sea state can be predicted based on the past history and current weather conditions and then runs a proper sensing algorithm, e.g., energy detection for a relatively calm sea and advanced sensing algorithm for higher sea states.

Acknowledgment

This work was supported by the CITRC (Convergence Information Technology Research Center) support program (NIPA-2013-H0401-13-1003) supervised by the NIPA (National IT Industry Promotion Agency) of the MKE. It was partially supported by Seoul R&BD Program (SS110012C0214831), the Converging Research Center Program and Basic Science Research Program through the NRF funded by the MEST(2009-0093695, 2010-0025316), and Special Disaster Emergency R&D Program from National Emergency Management Agency (2012-NEMA10-002-01010001-2012).

References

[1] J. S. Pathmasuntharam, J. Jurianto, P. Y Kong, Y. Ge, M. Zhou and R. Miura, "High Speed Maritime ship-to-ship/ shore Mesh Networks,"

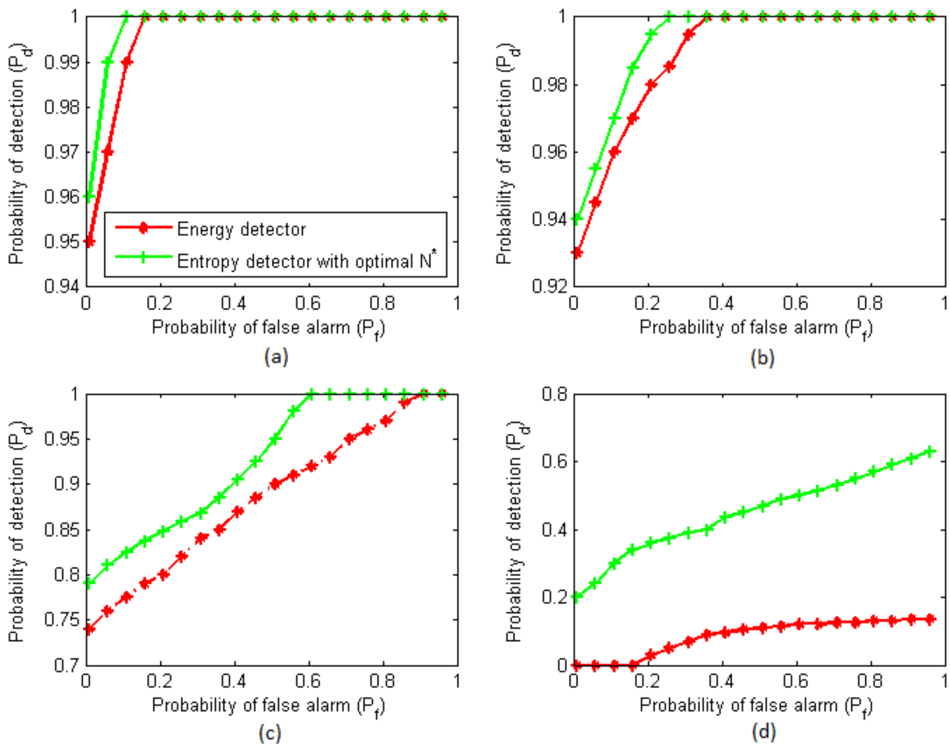

Fig. 4. Probability of detection vs. the probability of a false alarm at (a) Land Network, (b) Sea state 4, (c) Sea state 6 and (d) Sea state 7.

in Proc. IEEE Int. conf. on ITS Telecommunications, pp. 1-6, Sophia Antipolis, France, 2007.

[2] "First in the World: Wireless Mobile Wimax Access In Singapore Seaport Now a Reality," *6 March 2008. [Online].*

[3] F. Bekkadal, "Emerging maritime communications technologies," *in Proc. IEEE Int. conf. on ITS Telecommunications, pp. 358-363, Lille, France,* 2009.

[4] J. S. Pathmasuntharam, P-Y. Kong, M-T. Zhou, Y. Ge, H. Wang, C-W. Ang, W. Su, and H. Harada, "TRITON: high speed maritime mesh networks," *in Proc. IEEE Int. Symp. Pers., Indoor and Mobile Radio Commun., pp. 1-5, Cannes, France,* 2008.

[5] M-T Zhou and H. Harada, "Cognitive maritime wireless mesh/ ad hoc networks," *J. of Netw. and Comput. Appl., vol. 35, no. 2, pp. 518-526,* 2012.

[6] T. Yucek, and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *Commun. Surveys Tuts., vol. 11, no. 1, pp. 116-130,* 2009.

[7] I. F. Akildiz, B. F. Lo, and R. Balakrishan, "Cooperative spectrum sensing in cognitive radio networks: a survey," *Physical Commun., vol. 4, no. 1, pp. 40-62,* 2011.

[8] Y. L. Zhang, Q. Y. Zhang, and T. Melodia,"A frequency-domain entropy-based detector for robust spectrum sensing in cognitive radio networks," *Commun. Letters, vol. 14, no. 6, pp. 533-535,* 2010.

[9] S. L. Sabat, S. Srinu, A. Raveendranadh, and S. K. Udgata, "Spectrum sensing based on entropy estimation using cyclostationary features for Cognitive radio," *in Proc. IEEE Int. Conf. on Communication Systems and Networks (COMSNETS), pp. 1-6, Bangalore, India,* 2012.

[10] H. Xia, G. Zhang, and Y. Ding, "Spectral Entropy Based Primary User Detection in Cognitive Radio," *in Proc. IEEE Int. Conf. on Wireless Communications, Networking and Mobile Computing, pp. 1-4, Beijing, China,* 2009.

[11] W. J. Pierson, Jr and L. Moskowitz, "A proposed spectral form for fully developed seas based on the similarity theory of S. A. Kitaigorodskii," *J. Geosci. Res., vol. 69, no. 24, pp. 5181-5190,* 1964.

[12] W. Elliott, "Results of a VHF propagation study," *IEEE Trans. Antennas Propag., vol. 29, no. 5, pp. 808-811,* 1981.

[13] I. J Timmins and S. O'Young, "Marine Communication Channel Modeling using the Finite-Difference time domain method," *IEEE Trans. Veh. Technol., vol. 58, no. 6, pp. 2626-2637,* 2009.

[14] J.A. Snyman, "Practical Mathematical Optimization," *Springer Science+Business Media, Inc. New York: 2005.*

[15] IEEE Computer Society, "IEEE Std 802.22-2011 Part 22: Cognitive Wireless RAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications: Policies and Procedures for Operation in the TV Bands," IEEE Standard for Information technology, pp.1-672, 2011.