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Compressed Sensing Based Spectrum Detection for Maritime Cognitive Radio Networks

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Abstract: ***Maritime communication is important for information exchange between ships, location and tracking. Expeditious growth in marine communication has led to utilization of the allocated spectrum heavily. For example, Automatic Identification System (AIS) is a maritime system which uses VHF band for communication. Also, in recent times, wireless services are increasing, thereby require new spectral resources. Thus to efficiently utilize the spectral resources in maritime communication, Cognitive Radio (CR) can be employed. Spectrum for new service can be dynamically accessed along with the existing marine services. Thus to detect the spectrum availability, a compressed sensing (CS) based detection for maritime CR network (MCRN) is proposed in this paper and compared with the energy detection. Simulation results confirm the efficacy of the proposed algorithm.***

Keywords: ***Cognitive Radio, Maritime Communication, Spectrum Sensing, Compressed Sensing.***

I. INTRODUCTION

Initially maritime communication began using flag semaphores. Later, wireless radio frequency waves are being used for maritime communication between ship and the shore and between ships. Some of the popular satellite services to support maritime communication include INMARSAT, global mobile services by a British telecommunication company and International Cospas-Sarsat Programme, a search and rescue alert using satellite system [1]. VHF marine radios are used worldwide during emergency situations, in order to provide storm warning and for information broadcast. International Maritime Organization (IMO) requires that the wireless services in the sea should be improved to provide internet services for surveillance and control, passengers, security, etc., Thus novel solutions are essential to improve the maritime wireless access services in terms of both data rate and coverage aspects. However, spectrum availability is limited in maritime services and does not allow accommodating further improvements. To overcome this tradeoff, an efficient and novel solution is to use the cognitive radios for maritime communication [2].

Cognitive radios are transceivers that dynamically utilize the already allocated but unused spectrum. A foremost function of CR is to sense and identify whether a particular portion of the spectrum is occupied or vacant. When the allocated spectrum if found to be vacant, CRs use it for its own communication. CR is an intelligent technology proposed for terrestrial communication and can be extended to marine communication for efficient spectrum utilization. A maritime CR should be capable of detecting the spectrum availability in AIS VHF channels under varying channel conditions. To accomplish this task, spectrum sensing is the foremost function which is indispensable for a CR. Maritime cognitive radios perform spectrum sensing for detecting vacant spectral opportunities in AIS VHF communication [3]. Maritime services or applications in ships are considered as cognitive radios or secondary users. Spectrum sensing can be performed using matched filtering [4], energy detection [5] and cyclostationary feature based detection [6] approaches. Energy detection approach is very popular among all, for which prior knowledge about the primary signal is not required.

Wideband spectrum sensing becomes more challenging task which requires higher sampling rate Analog-to-digital convertor (ADC). This leads to long processing time and expensive hardware requirements. CS overcomes this problem by sampling the signal at a rate much below the Nyquist sampling rate depending on the sparsity [7]. There are different reconstruction algorithms in CS to reconstruct the original signal with fewer measurements. However, reconstruction of the original signal for spectrum sensing increases the complexity of the system. Hence, the objective of this paper is to propose a method to sense the spectrum using only the compressed measurements without reconstructing the original signal. Thus, this paper proposes a combination of CS framework without reconstruction and energy detection for the detection of PUs in MCRN.

II. MARITIME COGNITIVE RADIO SYSTEM

A. Maritime Spectrum Sensing Model and Architecture

The maritime spectrum sensing system model includes a licensed maritime communication referred to as PU and other maritime services referred to as SU or CR user. Multiple SUs sense the PU channel and arrive at a final conclusion regarding the availability of the PU. The SUs are coordinated by a SU base station.

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The SU near the coast can communicate to the base station by a direct wireless link and those are in the deep sea can communicate through a satellite link. Architecture for MCRN is given in Fig.1 which is followed from [8].

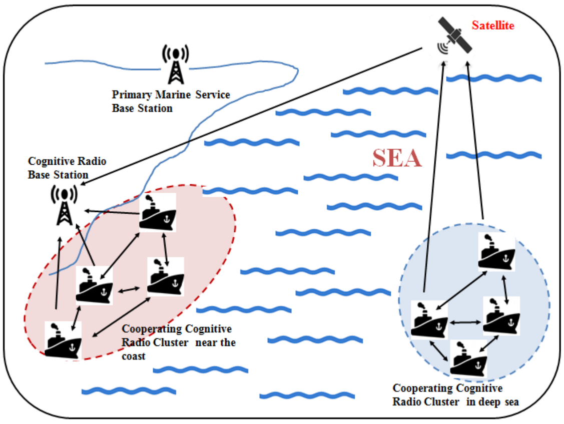

Fig.1. Architecture of MCRN.

B. Maritime Communication Channel

The wireless channel used for maritime communication is highly varying and the path loss experienced by a transmitted signal changes with the sea state. Sea state codes are defined by World Meteorological Organization (WMO) which is dependent on the characteristics of the sea condition and the sea wave height Table-1 [9]. The expression for pass loss using the height of the wave h (in meters) is given by [10],

$$P_l(h, f_o) = P_l(d_r) + 10\left\{\left(0.498\log_{10}(f_o) + 0.763\right)h + 2\right\}\log_{10}(d/d_r) + N_{f_o} \quad (1)$$

where $P_l(d_r)$ is the measured path loss at a reference location d_r, f_o is the frequency(GHz) and N_{f_o} is a random variable with zero mean and standard deviation σ_{f_o} given by, $\sigma_{f_o} = (0.157 f_o + 0.405)h$.

Table- I: WMO Sea State Code.

Sea Code	Height (m)	Sea State Characteristics
0	0	Calm and Glassy
1	0-0.1	Calm with rippled
2	0.1-0.5	Smooth with wavelets
3	0.5-1.25	Slight
4	1.25-2.5	Moderate
5	2.5-4	Rough
6	4-6	Very rough
7	6-9	High
8	9-14	Very high
8	>14	Phenomenal

III. COMPRESSED SPECTRUM SENSING

CS is a paradigm, known for its accurate recovery of sparse signals when sampled below Nyquist rate. A signal is said to be sparse if it has lesser number of non zero elements. An AIS VHF PU signal is considered sparse in frequency domain when a wideband sensing is employed. The compressed signal is usually represented as [7],

$$y = \varphi x \quad (2)$$

where x is the PU signal of size $N \times 1$, φ is known as the measurement matrix or sensing matrix of size $M \times N (M < N)$ and y is the compressed signal of size $M \times 1$. The signal received by the SU in marine environment is given by [3],

$$R_y(t) = y \times \sqrt{\frac{G}{PL(h, f)}} + w \quad (3)$$

where the G is the antenna gain in dB, $PL(h, f)$ is the path loss in dB experienced by the PU signal in the marine environment and w is the assumed to be Additive White Gaussian Noise (AWGN). To accurately recover the signal back, many optimization techniques have been proposed such as gradient descent, matching pursuit, L_1 norm minimization etc. Our aim is to sense the spectrum without reconstructing the received compressed signal. We also compare the spectrum sensing using compressed signal with that of spectrum sensing using reconstructed signal. Here we consider L_1 norm minimization for reconstruction. From the literature according to L_1 norm minimization, x can be recovered from y if the following optimization problem is solved,

$$x = \arg\min_x \|x\|_1 \quad \text{subject to } y = \varphi x \quad (4)$$

Presence of PU is determined by spectrum sensing using binary hypothesis model by SU without and without reconstruction respectively, as given by [4],

$$r(t) = \begin{cases} w(t), & \text{in case of } H_0 \\ R_y(t) + w(t), & \text{in case of } H_1 \end{cases} \quad (5)$$

$$r(t) = \begin{cases} w(t), & \text{in case of } H_0 \\ \hat{x} + w(t), & \text{in case of } H_1 \end{cases} \quad (6)$$

H_0 represents the hypothesis of idle spectrum and H_1 represents the hypothesis of busy spectrum. After CS, the signal energy over the PU spectrum is determined and compared against a suitable preset threshold. If the calculated energy value is greater than the preset threshold, then the PU is said to be occupied over the spectrum, else the primary spectrum is concluded available.

If the primary spectrum is available, SU can use the spectrum for its services. However, the SU should periodically monitor the primary spectrum. If the PU reoccupies the spectrum any time, the SU should immediately stop using the spectrum and can continue sensing the spectrum. In practice spectrum sensing techniques may led to error in the detection which can be classified into missed detection and false alarm. A missed detection occurs when the PU is present but the SU decides

that the spectrum is vacant which results in harmful interference to the PU.

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A false alarm occurs when PU is absent but the SU decides that the spectrum is occupied which lowers the spectrum utilization. Based on these definitions, the performance of spectrum sensing techniques is analyzed in terms of the probability of detection P_d and probability of false alarm P_f as given by,

$$P_d = \Pr\left(T(r) > \lambda / H_1\right) \quad (7)$$

$$P_f = \Pr\left(T(r) > \lambda / H_0\right) \quad (8)$$

where $T(r)$ is the energy of the signal received at the SU which is calculated using M samples and also known as test statistic given by [11],

$$T(r) = \sum_{i=i}^{M} |r(t)|^2 \quad (9)$$

The corresponding P_d and P_f are given by,

$$P_d = Q\left(\frac{\lambda - M\left(\sigma_x^2 + \sigma_w^2\right)}{\sqrt{2M\left(\sigma_x^2 + \sigma_w^2\right)}}\right) \quad (10)$$

$$P_d = Q\left(\frac{\lambda - M\sigma_w^2}{\sqrt{2M\sigma_w^2}}\right) \quad (11)$$

where *Q(.)* is the complementary distribution function of the standard Gaussian distribution, σ_x^2 is the average power of the received signal and σ_w^2 is the noise variance. The performance of the proposed detection scheme is evaluated using ROC curves and against SNR variations.

IV. SIMULATION RESULTS

The simulation for MCRN with sea wave movement model and pathloss model has been carried out using MATLAB. Pathloss of PU signal at different sea states are simulated which is shown in Fig.2. The wave height values for different sea states is tabulated in Table 1. The reference distance is set to 1m and the distance between the primary transmitter and the secondary receiver varies from 0 to 20 km. Path loss is severe at the higher sea states which cause harmful interference with PU. It is also noted a long sensing time is required to detect the presence of PU for sea states 7 and above which consumes more energy.

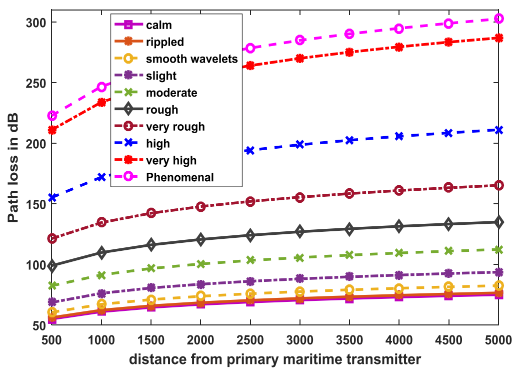

Fig.2. Path loss of PU signal for different sea states

In our work, VHF PU signal (161.975MHz and 162.025MHz) is chosen as the PU signal for which the power spectrum is obtained. The normalized input power level of the PU signal over a time period is shown in Fig.3. The SU performs CS to sense the PU and may employ suitable detection algorithms to decide the spectrum availability. Gaussian measurement signal is used for CS and the maritime channel is assumed with a sea state code of 4.

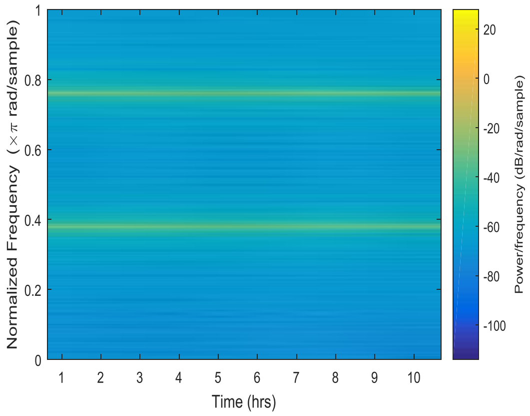

Fig.3. Input Power Level of Primary Signal

Power level against time of the compressed signal received at the SU without reconstruction is shown in Fig.4 (a). L_1 norm minimization is performed at SU to reconstruct the original signal and its power spectrum is shown in Fig.4 (b). Reconstruction using L_1 norm minimization is iterative process that consumes more time and increases the computational complexity which is not required for spectrum sensing. Spectrum sensing requires only the power or energy of the received signal and not the original data of the signal. From Fig.4 (a), it is inferred that the required energy for spectrum sensing can be obtained from compressed measurements without the reconstruction of the original signal. Hence spectrum sensing with compressed measurements efficiently reduces the computational complexity, processing time and cost of the system.

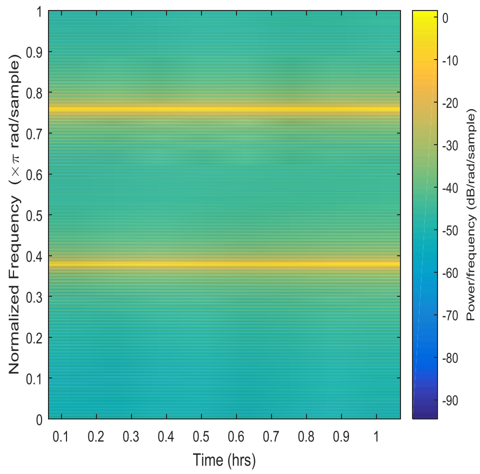

Fig.4. Power spectrum of PU signal sensed by SU using CS

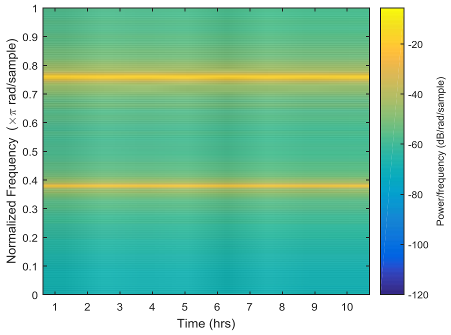

Fig.5. Power spectrum of PU signal recovered by SU using L_1 norm optimization

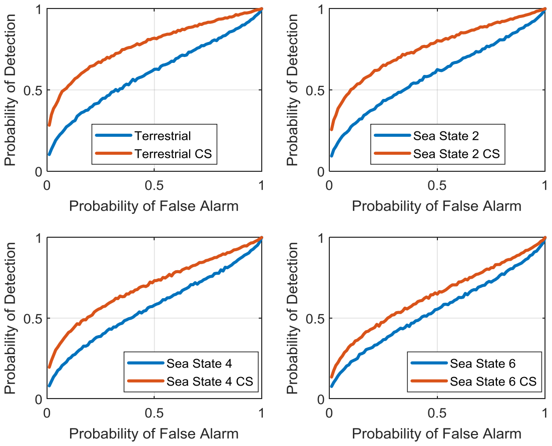

Fig.6. ROC performance of energy detection algorithm with and without CS

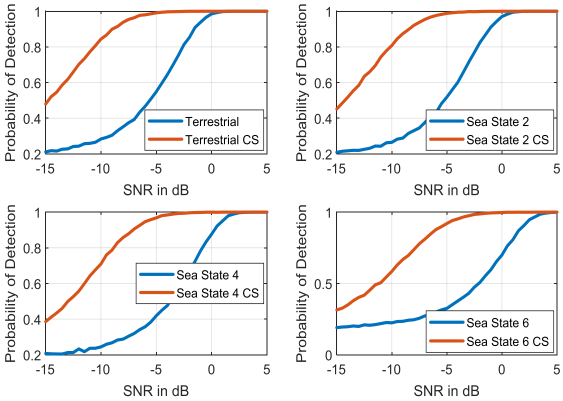

Fig.6. SNR performance of energy detection algorithm with and without CS

Fig.5 and Fig.6 shows the ROC and SNR performance of the proposed algorithm for both terrestrial and varying sea states with and without CS. In all the cases, the performance with CS is found to outperform than without CS. However, the performance also varies with varying sea state codes. It is observed from the results that the average improvement in P_d for a P_f value of 0.1 is 70%. Similarly at a SNR of 0dB, the average improvement in the detection is 12.7% and as SNR decreases the performance improvement increases.

V. CONCLUSION

An alternate solution for emerging wireless services and applications in maritime communication using CS based CR is proposed. AIS VHF class A and class B services are treated as primary radio. The wireless spectrum for other maritime services can be opportunistically obtained via CS based CR techniques. The use of CS also reduces the sensing duration and complexity as the spectrum availability can be detected based on reduced measurements. We have analyzed that CS can be employed up to a sea state code of 6. From the results, it is observed that the use of CS provides an improvement of 70% in detection performance. To further improve the detection performance, cooperative or distributed sensing among multiple SUs can be performed.

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Dr.K.Muthumeenakshi serves as an Associate Professor in the Department of Electronics and Communication Engineering. She was with SSN since January 2009. She received her B.E. in Electronics and Communication Engineering from Bharathiar University, M.E. in Applied Electronics and Ph.D. from Anna University Chennai. Her research interests include work on Signal processing, Spectrum sensing and Dynamic spectrum access issues in cognitive radios and RF Energy Harvesting techniques.