IDENTIFYING DATA INTERCHANGE FOR COGNITIVE RADIO NETWORKS THROUGH CLAMOR INCONSISTENCY INSECURITY

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ABSTARCT:

This paper proposes novel spectrum sensing algorithm, and examines the sensing throughput tradeoff for cognitive radio (CR) networks under noise variance uncertainty. It is assumed that there are one white sub-band, and one target sub-band which is either white or non-white. Under this assumption, first we propose a novel generalized energy detector (GED) for examining the target sub-band by exploiting the noise information of the white sub-band, then, we study the tradeoff between the sensing time and achievable throughput of the CR network. To study this tradeoff, we consider the sensing time optimization for maximizing the throughput of the CR network while appropriately protecting the primary network. The sensing time is optimized by utilizing the derived detection and false alarm probabilities of the GED. The proposed GED does not suffer from signal to noise ratio (SNR) wall (i.e., robust against noise variance uncertainty) and outperforms the existing signal detectors. Moreover, the relationship between the proposed GED and conventional energy detector (CED) is quantified analytically. We show that the optimal sensing times with perfect and imperfect noise variances are not the same. In particular, when the frame duration is 2s, SNR= −20dB, and each of the bandwidths of the white and target sub-bands is 6MHz, the optimal sensing times are 28.5ms and 50.6ms with perfect and imperfect noise variances, respectively.

INTRODUCTION:

In cognitive radio networks a secondary user is allowed to opportunistically utilize the vacant spectrum channels left by the primary user without interfering with their transmission. One of the key challenges for secondary users in cognitive radio networks is how to know when to occupy or leave the spectrum (i.e., the channels) for primary users' transmission. To tackle this problem, the secondary user must be capable of predicting in advance the channel availability of the primary user (i.e., whether the PU channels' status are "idle" or "busy") so that it can occupy or leave the channels for PU transmission. The spectrum occupancy prediction problem has been widely investigated, for example, the idea of predictive spectrum access was first introduced in [1], in which the authors utilize Hidden Markov Model (HMM) to solve the spectrum occupancy prediction problem. Later on, the HMM-based spectrum prediction model received great attention in the literature [2-4]. And, due to the fact that HMM-based approaches require a priori knowledge of the PUs' traffic pattern, other machine learning approaches such as neural network [5], Bayesian inference [6] and online support vector regression (SVR) [7] have been adopted for the prediction of PU channel availability. However, these prediction techniques consider only time-invariant PU model behaviors. While in real-world cognitive radio systems, PU traffic patterns can also exhibit time-variant traffic above-mentioned machine learning algorithms. On the other hand, the Bayesian online learning algorithm (BOL) [8] has a capability to track both time-variant and time-invariant dual-states switching time series behaviors. Motivated by the fact that the nature of the Pus channel state availability can be also modeled as dual-states switching time series, we propose a new spectrum occupancy (PUs channel state) prediction technique that utilizes BOL to perform PU channel availability prediction in cognitive radio network. In more details, we captured the PU channel state energy detection sequence using a time series that switches over the time between two different random distributions representing the PU channel state (i.e., PU idle or PU occupied). We then fed this time series as an observations sequence into a BOL prediction algorithm to estimate or predict in advance the point of the time when the change will occur between the two states of the time series so that SUs can adjust their transmission strategies accordingly. The experimental results show the effectiveness of the BOL algorithm in predicting the changing points of the time series that were generated to capture PU channel availability.

LITERATURE REVIEW:

"COOPERATIVE SPECTRUM SENSING UNDER NOISE UNCERTAINTY IN COGNITIVE RADIO"Spectrum sensing is the key technology in Cognitive Radio (CR) for primary user detection. Noise uncertainty in spectrum sensing will make the detector unreliable due to ”SNR walls”. In this paper, cooperative spectrum sensing with adaptive thresholds is proposed to improve the detection performance under noise uncertainty. In this algorithm, each secondary user will use a two-thresholds detector for local detection. The thresholds are chosen according to the noise uncertainty at each secondary user. After each detection, the detection results are fused to give the final decision. Computer simulation indicates that our proposed algorithm is robust to the changes of noise uncertainties at secondary users. It can achieve better performance than cooperative spectrum sensing with one threshold or two fixed thresholds when the noise uncertainties are not equal at each secondary user In opportunistic spectrum access (OSA), the spectrum of the licensed (primary) users is monitored and recycled by unlicensed (secondary) users to satisfy the demand for more bandwidth. It is the main idea and key technology in Cognitive Radio (CR) [1] which can improve the utilization of radio spectrum for wireless communications.. The spectrum is opportunistically reused by secondary users once the spectrum is spatiotemporal idle. The primary signal is monitored with spectrum sensing by the secondary users to avoid harmful interference with primary users during the spectrum reuse. Many spectrum sensing methods have been proposed. There are three types of spectrum sensing [2], energy detection [3], coherent detection [4] and cyclostationary feature detection [5]. A reliable detection is established on the perfect knowledge of the parameters of the environment and the primary users. However, in a real-world, these parameters can not be known to infinite precision. [6], [7] show that under noise uncertainty, there are SNR walls that prohibit the detection to be robust. It means that under some SNR, a reliable detection can not be achieved even increase the sample number to infinite. In [8], cooperative spectrum sensing is proposed to improve the detection performance under noise uncertainty. It shows that more secondary users are needed to obtain a reasonably low probability of detection. For bandwidth saving, two thresholds cooperative spectrum sensing is proposed in [9]. It can achieve a comparable performance with the algorithm in [8]. In this paper, we focus on the detection problem under noise uncertainty. Cooperative spectrum sensing with adaptive thresholds is proposed to improve the detection performance under noise uncertainty. In this algorithm, each secondary user will use a two-thresholds detector for local detection. The thresholds are chosen according to the noise uncertainty at each secondary user. After each detection, the detection results are fused to give the final decision. Computer simulation indicates that our proposed algorithm is robust to the changes of noise uncertainty at secondary users. It can achieve better performance than cooperative spectrum sensing with one threshold or two fixed thresholds when the noise uncertainties are not equal at each secondary user.

"Adaptive two thresholds based energy detection for cooperative spectrum sensing"

In cognitive radio networks, secondary users need to conduct spectrum sensing to properly detect the presence of primary signals that may have much lower power than noise plus interference power. In such a case, time-varying noise plus interference, which is briefly called noise uncertainty in this paper, can substantially degrade the sensing reliability of hard information combining (HIC) and soft information combining (SIC). To improve the sensing reliability in the circumstance with heavy noise uncertainty, we propose an adaptive two thresholds based energy detection and a two stage HIC based cooperative decision for cooperative spectrum sensing. The proposed sensing technique has shown better performance than conventional HIC and comparable performance with SIC when a small number of sensing nodes are used in spectrum sensing The remarkable growth of new wireless services and the rapid development of various radio access technologies have aggravated the spectrum scarcity and motivated the use of dynamic spectrum access (DSA) technologies. On the other hand, recent studies by spectrum regulators show that the licensed spectrum is largely underutilized. Cognitive radio (CR) has been increasingly regarded as an efficient solution for mitigating such imbalance between the spectrum scarcity and the low spectrum utilization efficiency [1]-[3]. Detection of presence of primary signal, which is usually called spectrum sensing (SS), is regarded as a critical technology in realizing cognitive radio communication and has been intensively investigated by far [4]-[8]. In a cognitive radio network, sensing nodes, simply called CRs here, conduct SS and the performance is mainly decided by (primary) signal to interference-plus-noise ratio (SINR) of signals received at CRs. At the same time, the interference depends heavily on communication circumstance and its power is time-varying at each CR. The timevaryinginterference leads to uncertainty of noise plus interference power and such feature is called noise uncertainty in this paper. In energy detection (ED) based SS, noise uncertainty increases the difficulty in setting the optimal threshold for a CR and thus degrades its sensing reliability [9]. Run-time estimation of time-varying noise plus interference power, which is called run-time noise estimation in the paper, is regarded as being effective in combating the noise uncertainty problem; however, it increases sensing duration and system complexity, and its sensing accuracy is limited in fast varying interference. Cooperative SS is also commonly used to mitigate the noise uncertainty problem. Hard information combing (HIC) and soft information combining (SIC) are the two classical cooperative SS techniques [10]-[11]. In HIC each CR measures the received signal power, reaches a binary decision and reports it to a coordinator; by hard combining the decisions the coordinator then makes a cooperative decision on presence or absence of primary signal. Instead of sending a binary decision, in SIC each CR sends directly the measured signal energy to the coordinator; the coordinator then calculates the mean value of measurement results and makes a cooperative decision. In a situation of having negative SINR and a small number of CRs, the noise uncertainty problem can not only lead to non-robust HIC but also substantially degrade sensing performance of SIC. In this paper, to realize more accurate detection of primary signal level by each CR in the circumstance with heavy noise uncertainty, we propose a new ED that uses three detection thresholds, including two thresholds newly defined based on upper and low bounds of the noise uncertainty range; we then further propose a two stage HIC strategy to improve the reliability of cooperative decision.

“SPECTRUM-SENSING ALGORITHMS FOR COGNITIVE RADIO BASED ON STATISTICAL COVARIANCES”Spectrum sensing, i.e., detecting the presence of primary users in a licensed spectrum, is a fundamental problem in cognitive radio. Since the statistical covariances of the received signal and noise are usually different, they can be used to differentiate the case where the primary user’s signal is present from the case where there is only noise. In this paper, spectrum-sensing algorithms are proposed based on the sample covariance matrix calculated from a limited number of received signal samples. Two test statistics are then extracted from the sample covariance matrix. A decision on the signal presence is made by comparing the two test statistics. Theoretical analysis for the proposed algorithms is given. Detection probability and the associated threshold are found based on the statistical theory. The methods do not need any information about the signal, channel, and noise power a priori. In addition, no synchronization is needed. Simulations based on narrow-band signals, captured digital television (DTV) signals, and multiple antenna signals are presented to verify the methods CONVENTIONAL fixed spectrum-allocation policies lead to low spectrum usage in many frequency bands. Cognitive radio, which was first proposed in [1], is a promising technology for exploiting the underutilized spectrum in an opportunistic manner [2]–[5]. One application of cognitive radio is spectral reuse, which allows secondary networks/users to use the spectrum allocated/licensed to the primary users when they are not active [6]. To do so, the secondary users are required to frequently perform spectrum sensing, i.e., detecting the presence of the primary users. If the primary users are detected to be inactive, the secondary users can use the spectrum for communications. On the other hand, whenever the primary users become active, the secondary users have to detect the presence of those users in high probability and vacate the channel within a certain amount of time. One communication system using the spectrum reuse concept is the IEEE 802.22 wireless regional area networks [7], which operate on the very high-frequency/ultrahigh-frequency bands that are currently allocated for TV broadcasting services and other services, such as wireless microphones. Cognitive radio is also an emerging technology for vehicular devices. For example, in [8], cognitive radio is proposed for underwater vehicles to fully use the limited underwater acoustic bandwidth, and in [9], it is used for autonomous vehicular communications. Spectrum sensing is a fundamental task for cognitive radio. However, there are several factors that make spectrum sensing practically challenging. First, the signal-to-noise ratio (SNR) of the primary users may be very low. For example, the wireless microphones operating in TV bands only transmit signals with a power of about 50 mW and a bandwidth of 200 kHz. If the secondary users are several hundred meters away from the microphone devices, the received SNR may be well below −20 dB. Second, multipath fading and time dispersion of the wireless channels make the sensing problem more difficult. Multipath fading may cause signal power fluctuation of as large as 20–30 dB. On the other hand, coherent detection may not be possible when the time-dispersed channel is unknown, particularly when the primary users are legacy systems, which do not cooperate with the secondary users. Third, the noise/interference level may change with time, which yields noise uncertainty. There are two types of noise uncertainty: 1) receiver device noise uncertainty and 2) environment noise uncertainty. The receiver device noise uncertainty comes from [10]–[12] the nonlinearity of components and the time-varying thermal noise in the components. The environment noise uncertainty may be caused by the transmissions of other users, either unintentionally or intentionally. Because of noise uncertainty, in practice, it is very difficult to obtain accurate noise power There have been several sensing methods, including the likelihood ratio test (LRT) [13], energy detection method [10]–[15], matched filtering (MF)-based method [11], [13], [15], [16], and cyclostationary detection method [17]–[19], each of which has different requirements and advantages/disadvantages. Although LRT is proven to be optimal, it is very difficult to use, because it requires exact channel information and distributions of the source signal and noise. To use LRT for detection, we need to obtain the channels and signal and noise distributions first, which are practically intractable. The MF-based method requires perfect knowledge of the channel responses from the primary user to the receiver and accurate synchronization (otherwise, its performance will dramatically be reduced) [15], [16]. As mentioned earlier, this may not be possible if the primary users do not cooperate with the secondary users. The cyclostationary detection method needs to know the cyclic frequencies of the primary users, which may not be realistic for many spectrum reuse applications. Furthermore, this method demands excessive analog-to-digital (A/D) converter requirements and signal processing capabilities Energy detection, unlike the two other methods, does not need any information of the signal to be detected and is robust to unknown dispersed channels and fading. However, energy detection requires perfect knowledge of the noise power. Wrong estimation of the noise power leads to an SNR wall and high probability of false alarm [10]–[12], [15], [20]. As pointed out earlier, the estimated noise power could be quite inaccurate due to noise uncertainty. Thus, the main drawback for the energy detection is its sensitiveness to noise uncertainty [10]–[12], [15]. Furthermore, while energy detection is optimal for detecting an independent and identically distributed (i.i.d.) signal [13], it is not optimal for detecting a correlated signal, which is the case for most practical applications In this paper, to overcome the shortcoming of energy detection, we propose new methods based on the statistical covariances or autocorrelations of the received signal. The statistical covariance matrices or autocorrelations of signal and noise are generally different. Thus, this difference is used in the proposed methods to differentiate the signal component from background noise. In practice, there are only a limited number of signal samples. Hence, the detection methods are based on the sample covariance matrix. The steps of the proposed methods are given as follows: First, the sample covariance matrix of the received signal is computed based on the received signal samples. Then, two test statistics are extracted from the sample covariance matrix. Finally, a decision on the presence of the signal is made by comparing the ratio of two test statistics with a threshold. Theoretical analysis for the proposed algorithms is given. Detection probability and the associated threshold for the decision are found based on the statistical theory. The methods do not need any information of the signal, channel, and noise power a priori. In addition, no synchronization is needed. Simulations based on narrow-band signals, captured digital television (DTV) signals, and multiple antenna signals are presented to evaluate the performance of the proposed methods

"Marginalized adaptive particle filtering for nonlinear models with unknown time-varying noise parameters" Knowledge of the noise distribution is typically crucial for the state estimation of general state-space models. However, properties of the noise process are often unknown in the majority of practical applications. The distribution of the noise may also be non-stationary or state dependent and that prevents the use of off-line tuning methods. For linear Gaussian models, Adaptive Kalman filters (AKF) estimate unknown parameters in the noise distributions jointly with the state. For nonlinear models, we provide a Bayesian solution for the estimation of the noise distributions in the exponential family, leading to a marginalized adaptive particle filter (MAPF) where the noise parameters are updated using finite dimensional sufficient statistics for each particle. The time evolution model for the noise parameters is defined implicitly as a Kullback–Leibler norm constraint on the time variability, leading to an exponential forgetting mechanism operating on the sufficient statistics. Many existing methods are based on the standard approach of augmenting the state with the unknown variables and attempting to solve the resulting filtering problem. The MAPF is significantly more computationally efficient than a comparable particle filter that runs on the full augmented state. Further, the MAPF can handle sensor and actuator offsets as unknown means in the noise distributions, avoiding the standard approach of augmenting the state with such offsets. We illustrate the MAPF on first a standard example, and then on a tire radius estimation problem on real data. Systems with unknown and potentially time-varying noise statistics are common in many applications, and a lot of effort was invested into estimation of the noise properties. Estimation of the covariance matrices for the Kalman filter was addressed in Mehra (1972), where different approaches have been systematically classified into the following categories: Bayesian, maximum likelihood, correlation and covariance matching. Traditionally the problem has been addressed for linear systems; see e.g., Kosanam and Simon (2004) and Liang, An, Zhou, and Pan (2004). A correlation based adaptive Kalman filter for noise identification using the weighted least squares criterion has been proposed in Oussalah and De Schutter (2000), while an asymptotic (in time) maximum likelihood estimate has been proposed in Maine and Iliff (1981). On the other hand, the Bayesian approach has been used, for example, in Li and Bar-Shalom (1994) and Särkkä and Nummenmaa (2009). In Li and Bar-Shalom (1994), the nonstationary noise statistics are estimated using the so called IMM method, while an adaptive Kalman filter based on variational Bayesian methods is used in Särkkä and Nummenmaa (2009). An adaptive sequential estimation with unknown noise statistics has been proposed in Myers and Tapley (1976). Estimation of a state dependent covariance matrix using the marginalized particle filter approach has been considered by Šmídl (2008), where the covariance matrix is treated as an additional state, for which a state transition equation has been defined. Many of the parameter estimation methods in particle filtering rely on state augmentation technique eg., Liu and West (2001) and Storvik (2002). Such approaches have two main disadvantages. One is the increase in the state dimension which should be avoided in particle filters as they suffer from the curse of dimensionality. The second is the error accumulation in case of static parameters estimation as addressed in Andrieu, Doucet, and Tadic (2005). In this paper, we are concerned with a more general case of non-stationary noise characteristics belonging to the exponential family. Specifically, we focus on systems with slowly varying parameters, where the term ‘‘slowly varying’’ is defined as a constraint on Kullback–Leibler divergence rather than an explicit random-walk model. We show that under such a constraint, explicit parameter evolution is not necessary and the predictive density of the parameter can be replaced by the maximum entropy estimate. The estimate is shown to be closely related to the classical technique of exponential forgetting (Kulhavý&Zarrop, 1993). Since the result of exponential forgetting is within the exponential family, the concept of sufficient statistics can be used to obtain analytical posterior. Analytical posteriors are necessary for marginalization, which results in efficient particle filtering algorithms (Schön, Gustafsson, &Nordlund, 2005) The approach is closely related to the published results for the estimation of stationary noise parameters using marginalized particle filters e.g. by Bordin and Bruno (2008), Carvalho, Johannes, Lopes, and Polson (2010), Djuric and Miguez (2002) and Storvik (2002). The system considered in Bordin and Bruno (2008) is a specific model for a binary output and it is partially linear. The approach in Djuric and Miguez (2002) is focused on Gaussian parameters, while Storvik (2002) has extended this approach to general exponential family models. However, for the stationary parameters, the approach is known to suffer from error accumulation, as pointed out in Chopin et al. (2010). We show that this problem does not arise in our case. Specifically, the forgetting used in the prediction stage introduces the exponential forgetting property of the system that is well known to mitigate the path degeneracy problem (Crisan&Doucet, 2002). Our experiments show that the proposed method is capable of estimating the unknown parameters of the measurement noise as well as the process noise even for highly nonlinear models. This article is an extended version of our previous work presented in Saha, Özkan, Gustafsson, and Šmídl (2010).

“**Spectrum Sensing for Cognitive Radios in Time-Variant Flat-Fading Channels: A Joint Estimation Approach”**Most of the existing spectrum sensing schemes utilize only the statistical property of fading channels, which unfortunately fails to cope with the time-varying fading channel that has disastrous effects on sensing performance. As a consequence, such sensing schemes may not be applicable to distributed cognitive radio networks. In this paper, we develop a promising spectrum sensing algorithm for time-variant flat-fading (TVFF) channels. We first formulate a dynamic state-space model (DSM) to characterize the evolution behaviors of two hidden states, i.e., the primary user (PU) state and the fading gain, by utilizing a two-state Markov process and another finite-state Markov chain, respectively. The summed energy, which serves as the observation of DSM, is employed for the ease of implementation. Relying on a Bayesian statistical inference framework, the sequential importance sampling based particle filtering is then exploited to numerically and recursively estimate the involved posterior probability, and thus, the PU state and the fading gain are jointly estimated in time. The estimations of two states are soft-outputs, which are successively refined with a designed iterative approach. Simulation results demonstrate that the new scheme can significantly improve the sensing performance in TVFF channels, which, in turn, provides particular promise to realistic applications COGNITIVE RADIO (CR) enables dynamic spectrum access (DSA) and opportunistic transmission of the secondary user (SU) in authorized primary frequency bands [1], which is of great promise to promote the efficiency of frequency utilization and hence alleviate the scarcity of spectrum resources [2]–[4]. Based on a real-time awareness of operation surroundings and the bandwidth availability, CR can intelligently adapt its functionalities to best accommodate the current wireless environment and simultaneously best serve its users [2]. One of the most fundamental issues to be considered in CRs is spectrum sensing, which aims to identify the unknown working states (i.e., active or sleep) of primary user (PU) and, therefore, makes the SUs ready for the opportunistic use of vacant primary bands [5], [6]. Traditional spectrum sensing techniques include energy detection (ED) [7], matched filter (MF) detection [8] and cyclostationary feature detection [10], [11], which in practice may have different advantages and requirements [5], [6]. ED excludes any a priori information of PU signals and, therefore, is robust and simple, which yet has an uncompetitive sensing performance [9], [12]. In coherent MF detection, pilot signals are employed to achieve the optimum detection performance [8], which, however, may impractically require the perfect timing and the complete waveform (or sequence) information of PUs. By concentrating on the spectrum correlation function (SCF) of primary signals, cyclostationary detection may identify spectrum holes even in extremely low signal to noise ratio (SNR). However, the exhaustive search for unknown cyclic frequency makes it computationally intensive [5] Recently, wavelet analysis [13] and compressive sensing are introduced to perform multi-band sensing [14]. By properly exploiting the statistical information of primary signals, a covariance-matrix based sensing algorithm is developed in [15], which has been proven to be efficient and robust in realistic applications [16]. It is noted that, by exploiting statistical correlations of PU signals (e.g., the time or spatial correlations), this covariance-based method may significantly improve the sensing performance. As suggested, the probabilistic property of PU's states may be utilized either to optimize the sensing strategy and thereby maximize the throughput of CR networks [17], or to design the sensing algorithm and further enhance the sensing performance [18]. From a general system point of view, the spectrum sensing may involve three stochastic processes, i.e., the contaminated PU signal x (or noise z), the random channel state α and the observation (or decision) variable y (e.g., the summed energy). The observation variable is closely coupled with the other two random components, relying on which the spectrum sensing is realized. Practically, the channel state is independent of the PU state, as far as the purpose of spectrum sensing is concerned. Hence, the unknown channel is only a latent variable for CR devices. It should be noteworthy that, nevertheless, such a latent variable will significantly increase the uncertainty of the observation variable y and, therefore, may have remarkable effects on the sensing performance. For the emerging CR applications with mobile devices (e.g., LTE-A and 802.11n), the channel may become time-variant [19], [20], making the spectrum sensing even tougher. In practice, the time-varying fading is not always an unfavorable factor. For example, the PU signal cannot be detected in extremely low SNRs regions. With proper configurations, however the statistical property introduced by time-varying fading effects may distinguish PU signals from the background Gaussian noise [21]. In such cases, the timevarying fading would become beneficial. In this investigation, notice that, the slow-varying fading is mainly considered, i.e., the dynamic gain remains invariant during a sensing slot, which may unfortunately degrade the performance.

"**Deep Sensing for Space-Time Doubly Selective Channels: When a Primary User is Mobile and the Channel is Flat Rayleigh Fading,"**The unrestrained mobility and dynamic spectrum sharing are considered as two key features of next-generation communications. In this paper, spectrum sensing in mobile scenarios is investigated, which faces still great challenges as both the mobile location of primary-user and fading channel will become time-variant. Such two uncertainties would arouse remarkable fluctuations in the strength of received signals, making most existing sensing schemes invalid. To cope with this exceptional difficulty, a novel paradigm, i.e. deep sensing, is designed, which estimates the time-dependent flat-fading gains and primary-user's mobile positions jointly, at the same time of detecting its emission status. All three hidden states involved by the space-time doubly selective scenario are taken into accounts. A unified dynamic state-space model is established to characterize the dynamic behaviors of unknown states, in which the time-dependent flat fading is modeled as a stochastic discrete-state Markov chain. A Bayesian approach, premised on a formulation of random finite set, is suggested to recursively estimate primaryuser's unknown states accompanying two others link uncertainties. In order to avoid the mis-tracking of the mobile positions, which is caused either by the incessant disappearance of primary-user or time By promoting the spectrum utilization of authorized frequency and thereby alleviating the spectrum scarcity, dynamic spectrum sharing (DSS) provides the great promise to next-generation communications [1], which may pave a way for the development of new wireless services without allocating extra frequency [2], [3]. For the emerging indoor applications, e.g. the license assisted access (LAA) to the WiFi band discussed in LTE-U [3], [4], a primary user (PU) can be a smartphone or a personal digital assistant (PDA) that will be move around in the local region. For other outdoor applications, e.g. the cognitive wireless sensor networks (C-WSN), the PU may be a mobile device occupying the primary band. It is recognized that, except for the occupancy status of primary band which is usually acquired via spectrum sensing techniques, the mobile locations of PU and the time-dependent channels will be of great significance to the performance enhancement of cognitive radios (CRs) [5], [17]. When it comes to identifying PU's unknown states in complex electromagnetic environments, however, such two participating random components (i.e. the mobility of PU's locations and the variation of fading channels) will bring great challenges to the practical deployment of spectrum sensing. Spectrum sensing, i.e. the real-time monitoring of the presence or absence of PU, is formulated essentially as a detection or hypothesis-test problem [7]. Since the advent of CRs, various sensing algorithms of different advantages and requirements have been developed [7]–[10]. Most traditional schemes, e.g. energy detector (ED) [11], [12], unfortunately are vulnerable to information uncertainties, e.g. the large-scale space-varying path loss or meso-scale time-varying fading channel. As suggested by [12], [13], the fading effect, given the a priori probability density function (PDF), will be marginalized out. By focusing simply on its instantaneous random behavior, this commonly used technique, however, ignores the correlation of time-varying flat fading [13]. Thus, it will be less competitive, in consideration of tracking time-dependent channels and further exploiting the underlying dynamic property. As far as the space-time doubly selective channels are concerned, i.e. with a mobile PU and variant channel fading, realistic observed signals will show remarkable fluctuations, which makes most existing sensing schemes invalid. The tracking of PU's locations, on the other hand, belongs to another parameters estimation issue. Traditional techniques include the externally aided positioning and the passive localization [14]. The first approach relies on specific external systems, e.g., global positioning system (GPS) or ultra-wideband [15]. The second method, in contrast, estimates the mobile positions by exploiting the information of observations, e.g., the received signal strength (RSS) [16] or the time of arrivals (ToAs) (or maybe the hybrid information) [17]. It is noteworthy that, for CR applications, usually most external systems will be impractical. Moreover, the localization of a mobile PU has to be accomplished in a non-coordinated manner and, thus, the available information will be very limited (e.g., only RSS may be used). The innate reason is that a PU endowed with the absolute priority (on its authorized spectrum) is not bound to accommodate the inferior secondary users (SUs) For a space-time doubly selective scenario, one has to deal with a more complicated mixed detection and estimation problem. The principal challenge is that the detection process (of PU's emission status) and the other estimation process (of two related link uncertainties) will be mutually interrupted. Unlike traditional joint estimation and detection problem [18], the RSS emitted by a PU will disappear randomly attributed to the dynamic switching of its occupancy status, making the acquisition of PU's moving positions and time-dependent channels even tough. To be specific, an erroneous PU's state will misguide the inference (or estimation) of its mobile positions accompanying the fading channels, which, in turns, will definitely harass the next round of detection. Most existing schemes, designed either for pure sensing or estimating problems, fail to take such coupling and transitive interruptions into account, which may become less attractive to the spectrum-location awareness application

IMPLIMENTATION

In this paper we have referred the mathematical model of Shoukang Zheng. In spectrum sensing, there are two hypotheses: H0 for the hypothesis that the PU is absent and H1 for the hypothesis that the PU is present. There are two important design parameters for spectrum sensing: probability of detection (PD), which is the probability that SU accurately detects the presence of active primary signals, and probability of false alarm (PF), which is the probability that SU falsely detects primary signals when PU is in fact absent. We define

Spectrumutilization=P(H0)(–PF)+P(H1)PD

And normalized

SU throughput= P(H0)(1– PF)

Respectively.

Note that P(H1)PD is PU throughput when there are primary signals and the SUs detect the presence of the of the primary signals. To determine whether the spectrum is being used by the primary user, the detection statistic TD is compared with a predetermined threshold ϵ. Probability of false alarm PF is the probability that the hypothesis test chooses H1 while it is in fact H0: PF = P(TD > ϵ| H0). Probability of detection PD is the probability that the rest correctly decides H0 when it is H1: PF = P(TD > ϵ| H1). To determine whether the spectrum is being used by the primary user, the detection statistic TD is compared with a predetermined threshold ϵ. Probability of false alarm PF is the probability that the hypothesis test chooses H1 while it is in fact H0: PF = P(TD > ϵ| H0). Probability of detection PD is the probability that the rest correctly decides H0 when it is H1: PF = P(TD > ϵ| H1).

BAYESIAN DETECTOR (ABD) STRUCTURE THROUGH THE APPROXIMATIONS IN THE LOW AND HIGH SNR REGIMES:

We give the theoretical analysis (detection performance and threshold) for the suboptimal detector to detect complex MPSK (M = 2 and M > 2) in low SNR regime and compare with the results for real BPSK primary signals.

A .APPROXIMATION IN THE LOW SNR REGIME:

We study the approximation of our proposed detector for MPSK modulated primary signals in the low SNR regime

$$\sum_{k=0}^{N-1} ln(\sum_{n=0}^{M/2} \cosh(v_n(k))$$

Through approximation, the detector structure becomes:

$$T_{L\text{-}ABD\text{-}1}=\frac{1}{N}\sum_{K=0}^{N-1}|r(k)|^2 \gtrless \frac{N0}{Y}\left(Y+\frac{ln€}{N}\right)$$

Above detector uses the real part of the received signal as input and has the same structure as the suboptimal detector for BPSK signals.

B. APPROXIMATION IN THE HIGH SNR REGIME

We consider the high SNR regime in this section.

When x≫0,cosh(x)≈e^{x}/2 or when

x≪0, cosh(x)≈e^{-x}/2

The detector structure becomes

$$T_{H\text{-}ABD}=\sum_{K=0}^{\frac{M}{2}-1}(ln(\sum_{n=0}^{\frac{M}{2}-1} e^{\frac{2}{N)}Ҝ[r(k)h^*e\text{-}j\Psi n(k)}))$$

$$\gtrless \gamma+\ln M$$

A special case of MPSK signals, we assume a real signal model for BPSK modulated primary signals. The suboptimal BD detector employs the sum of received signal magnitudes to detect the presence of primary signals in the high SNR regime, which indicates that energy detector is not optimal in this regime.

1. FALSE ALARM PROBABILITY

The false alarm probability, is

$$P_y = P(T_{L\text{-}ABD\text{-}1} > \frac{N0}{2}(\gamma + \frac{ln€}{N})|H(0)|$$

$$= Q(\frac{\frac{N0}{y}\left(y + \frac{ln€}{N}\right) - \mu}{\sigma})$$

$$= Q(\frac{ln\epsilon}{r\sqrt{N}})$$

2. DETECTION PROBABILITY

The detection probability is

$$P_D = P(T_{L\text{-}ABD\text{-}1} > \frac{N0}{2}(\gamma + \frac{ln€}{N})|H(1)|$$

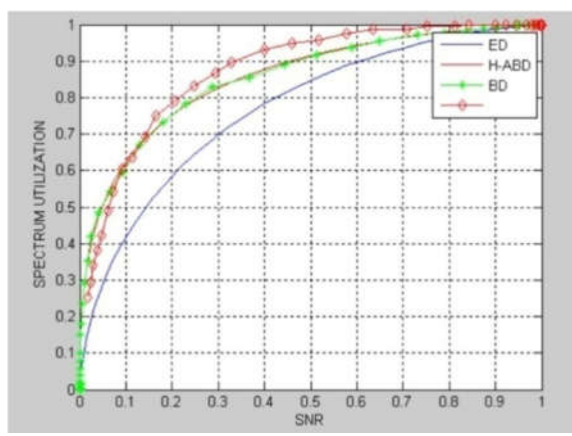
$$= Q(\frac{\frac{N0}{y}\left(y + \frac{ln€}{N}\right) - \mu}{\sigma})$$

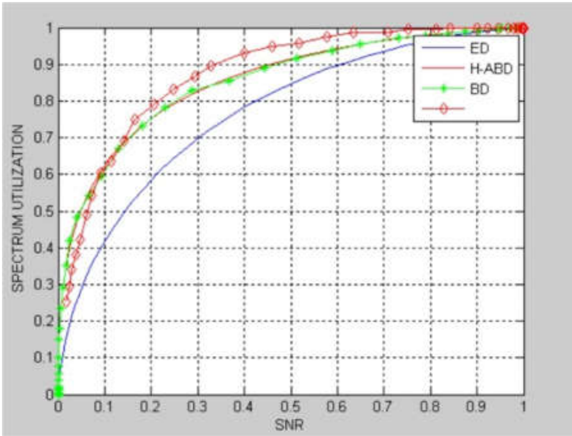
$$= Q(\frac{ln\epsilon - N\gamma 2}{r\sqrt{N(1+2\gamma N)}})$$

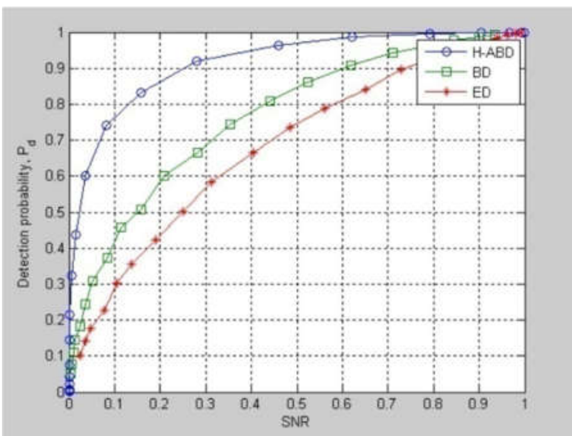
III.APPLICATIONS

Geo-location and Networking Applications: New capabilities are enabled when a CR knows where it is and where it is going. This information may be obtained through dedicated sensors such as an Inertial Navigation Unit, a GPS receiver, or through relative geo-location techniques built into the waveforms or configuration of an SDR channel to receive and process GPS signals. An inertial navigation unit keeps track of location relative to an initial known location through the use of accelerometers and time. The accuracy of this technique deteriorates in time, but re-synchronization with GPS receivers mitigates this characteristic. Through a combination of Inertial Navigation and GPS, a CR can sense its location with good precision, even indoors. from using the CR. Since a radio is usually used for voice communications, there is a microphone in the system. The captured signal is encoded with a Vo Coder and transmitted. The source radio can authenticate the user and add the known identity to the data stream.

SIMULATION RESULTS:







CONCLUSION:

The dynamic spectrum access, which is one of the applications of cognitive radio technology, has been observed as a promising solution to the problem of radio spectrum scarcity and underutilization by introducing the opportunistic usage of licensed frequency bands that are not efficiently utilized by licensed owners. Following the general belief that spectrum sensing is the key functionality to enable DSA, this research work focused on issues of spectrum sensing. The thesis discussed merits and demerits of most of the current detection methods or algorithms presented in literature. After a careful, neutral and constructive analysis of most of the current detection methods in literature, it showed that none of the methods can adequately and reliably detect all forms of primary radio signals in a cognitive radio environment.

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