Kalman Filter Enhanced Parametric Classifiers for Spectrum Sensing Under Flat Fading Channels

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Abstract. In this paper we propose and investigate a novel technique to enhance the performance of parametric classifiers for cognitive radio spectrum sensing application under slowly fading Rayleigh channel conditions. While trained conventional parametric classifiers such as the one based on K-means are capable of generating excellent decision boundary for data classification, their performance could degrade severely when deployed under time varying channel conditions due to mobility of secondary users in the presence of scatterers. To address this problem we consider the use of Kalman filter based channel estimation technique for tracking the temporally correlated slow fading channel and aiding the classifiers to update the decision boundary in real time. The performance of the enhanced classifiers is quantified in terms of average probabilities of detection and false alarm. Under this operating condition and with the use of a few collaborating secondary devices, the proposed scheme is found to exhibit significant performance improvement with minimal cooperation overhead.

Keywords: Cognitive radio · spectrum sensing · Kalman filter · machine learning · fading channels

1 Introduction

Cognitive radio (CR) is an enabling technology for dynamic spectrum access that will form an integral part of future wireless devices [1]. A core requirement for the successful implementation of CR system is spectrum sensing. It enables CR devices to detect the presence or absence of primary user's (PU) signal in the licensed frequency bands so that secondary users (unlicensed users) can opportunistically utilize these frequency bands in a manner that no disruptive interference is caused to the PU's transmissions [1], [2]. Over the last one decade, several techniques have been proposed for performing spectrum sensing in CR systems, the most widely used of which are the energy detection, matched filtering and cyclostationary detector schemes [3].

In the energy detection method, during sensing interval the secondary user (SU) computes the accumulated energy of the signal received at its terminal

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within the band of interest and compares the result to the measurement obtained for the ambient noise. Although the technique has great potential for ubiquitous applications due to its relative simplicity and capability for blind signal detection, its performance often degrade when there is uncertainty about the actual ambient noise power [2], [3]. Matched filtering technique is implemented by correlating the received signal and known PU signal and the outcome is used as a basis for deciding whether the PU signal is present or not [4]. The scheme is capable of yielding excellent detection performance when the waveform of the PU signal is known apriori and there is perfect knowledge of the PU-SU channel. Evidently, this technique can not be successfully used in an alien radio frequency environment where a priori knowledge of the PU signal is lacking. Another constraint on the use of the method is that the PU and SU must be perfectly synchronized during sensing time which would be difficult to achieve especially when the signal-to-noise ratio (SNR) of the PU-SU channel is low. Cyclostationary detectors are built to take advantage of known, unique features that are usually present in transmitted PU signals (e.g. cyclic prefix, spreading codes, modulated carriers, etc.) which are repetitive in nature by using them as signatures for detecting the PU signal's presence or absence. Although the technique offers robust performance in the presence of noise uncertainty and low SNR, its use is limited to applications where the signal characteristics of the PU is known apriori which makes it impractical for use in scenarios involving frequency re-use. It also requires long sensing time and is characterized by high computational complexity [2].

In fairly recent times, machine learning (ML) techniques have gained attention for solving the spectrum sensing problem and the performance evaluation of this approach is found to be better than most of the traditional sensing methods. For example in [5], semi-supervised parametric classifiers based on the K-means clustering and expectation-maximization (EM) algorithms are proposed. The supervised support vector machine (SVM) binary classifier and K-nearest neighbour (kNN) techniques are also proposed in [4] and [5] while the unsupervised variational Bayesian (VB) learning based method is presented in [6]. The general idea behind all these ML schemes is to train the SUs by using features that are derived from the traffic pattern in the licensed band of interest so that if the SUs are operated in an environment similar to the one captured by the training features, the SUs can use the knowledge of the traffic pattern that has been acquired to distinguish between when the channel is being occupied by the PU and otherwise [7]. It should be noted, however, that in practical scenarios for the deployment of CRs, the SU or PU may be physically mobile and as such the channel conditions characterizing the training and operating environments may differ, thereby the CR might fail to reliably and efficiently detect the true status of the PU's activities under monitoring.

To the best of our knowledge, the deployment of parametric classifiers by mobile SUs for spectrum sensing purpose under time varying channel conditions has not been considered in the literature. In this paper, we investigate the performance of SUs that depend on these classifiers for spectrum sensing under flat fading channels and propose a novel Kalman filter channel estimation based technique for enhancing their performance under these practical operating conditions.

The rest of the paper is as organized as follows. The problem statement is presented in section 2. In section 3, we describe the system model, assumptions and proposed algorithms. The simulation results obtained are discussed in section 4 followed by conclusion in section 5.

2 Problem Statement

A spectrum sensing network consisting of a fixed PU transmitter (PU-TX), a collaborating sensor node (CSN) co-locating with the PU, N PU receivers (PU-RX), a secondary base station (SBS) which plays the role of a data clustering center as well as the SUs' coordinator and M SUs as illustrated in Fig. 1 is considered. It is assumed that the PU's activity is such that it switches alternately between active and inactive states allowing the SUs to be able to opportunistically use its dedicated frequency band and operate within the PU's coverage area. During the training phase, all SUs sense the energy of the PU-SU channel at their respective locations during both states and report it to the SBS where clustering is performed and appropriate decision boundary is generated. It is assumed that the training data from individual SU is independent but identically distributed.

Let us suppose that based on the decision boundary that is generated from the training data, the PU has been declared to be inactive while all the SUs are stationary. Consider also that SU-c3 that is initially at point 'A' is using the PU's band while having to transit to point 'B' as shown. We assume that the channel condition characterizing the SU's trajectory is flat fading (e.g. traveling through a heavily built-up urban environment). This description equally applies where multiple mobile SUs share the PU's band and are able to cooperate. Since the training process of a learning technique normally takes a long time, under this scenario it is impractical for the mobile SU(s) to undergo re-training while in motion owing to the dynamic nature of the channel gain and if sensing information is exchanged among SUs, it could be received incorrectly due to the channel fading and noise resulting in performance loss [8],[9]. In addition, significant amount of energy and other resources are required to communicate sensing results periodically to other users and in a bid to conserve resources, SUs may prefer not to share their results [10]. To be able to detect the status of the PU activities correctly and efficiently, the onus is therefore on the individual mobile SU as it travels to cater to making well informed decision by dynamically adjusting its decision boundary at the SBS in a manner that the changes in channel conditions are taken into consideration, doing so with minimal cooperation overhead.

To address this challenge, in this paper we propose a framework whereby each SU incorporates a channel tracking sub-system that is based on the Kalman filtering algorithm which enables the SU to obtain an online, unbiased estimate of the true channel gain as it travels. The estimated channel gain can then be used to generate energy features for updating its decision boundary in real time. To investigate the capability of the proposed scheme, without loss of generality, we adopt the energy vectors based K-means clustering platform earlier proposed in [5] due to its simplicity.

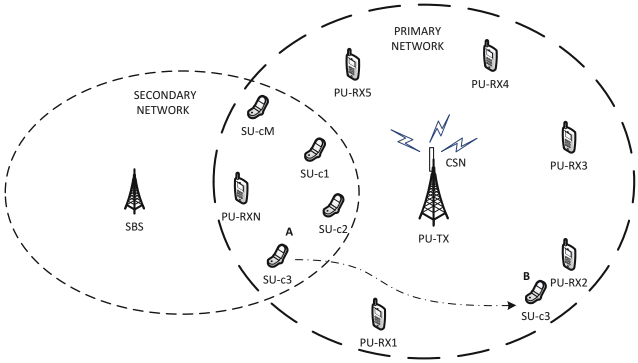

Fig. 1. A spectrum sensing system of a primary user and mobile secondary users networks.

3 System Model, Assumptions and Algorithms

Consider that the PU transmitter is located at a coordinate $\mathbf{x}_{pu}$ as shown in Fig. 1 and the mobile SU of interest SU-c3, is located initially at $\mathbf{x}_{su}^m$. During the training period, all SUs carry out sensing of the PU's channel at their respective locations and collectively report the estimated energy to the SBS where K-means clustering is performed and the cluster centroids are computed. The jointly reported sensing data can be used to obtain a high-dimensional decision plane at the SBS and can enable immobile SUs to be able to take advantage of space diversity and contain hidden node problem. Prior to SU-c3 being in motion, let $\phi(\mathbf{x}_{su}^m, n)$ represent the channel gain between the PU-TX and SU-c3 at a time instant n. Given that the PU signals are statistically independent, an estimate of the discrete-time signal received at the SU-c3 terminal can be written as

$$x_m(n) = \begin{cases} s(n)\phi(\mathbf{x}_{su}^m, n) + \eta_m(n), & H_1 : PU\ present \\ \quad \eta_m(n), & H_0 : PU\ absent \end{cases} \tag{1}$$

where the channel coefficient $\phi(\mathbf{x}_{su}^m, n)$ is assumed to be zero-mean, unit-variance complex Gaussian random variable whose magnitude squared is the power attenuation $P^{att}_{\mathbf{x}_{pu}\to\mathbf{x}_{su}^m}$, between PU-TX and SU-c3 which can be described by

$$\begin{aligned} P^{att}_{\mathbf{x}_{pu}\to\mathbf{x}_{su}^m} &= |\phi(\mathbf{x}_{su}^m, n)|^2 \\ &= L_p(\|\mathbf{x}_{pu} - \mathbf{x}_{su}^m\|_2) \cdot \delta_{\mathbf{x}_{pu}\to\mathbf{x}_{su}^m} \cdot \gamma_{\mathbf{x}_{pu}\to\mathbf{x}_{su}^m}, \end{aligned} \tag{2}$$

where $\|\cdot\|_2$ implies Euclidean norm, $L_p(\rho) = \rho^{-d}$ is the path loss component over distance ρ, d is the path loss exponent, $\delta_{\mathbf{x}_{pu}\to\mathbf{x}_{su}^m}$ is the shadow fading component and $\gamma_{\mathbf{x}_{pu}\to\mathbf{x}_{su}^m}$ represents the small scale fading factors. The remaining parameters in (1) are $s(n)$ which is the instantaneous PU signal assumed to be circularly symmetric complex Gaussian with mean zero and variance $\mathbb{E}|s(n)|^2 = \sigma_s^2$ and $\eta_m(n)$, which is assumed to be an independent and identically distributed complex zero-mean Gaussian noise with variance $\mathbb{E}|\eta_m(n)|^2 = \sigma_\eta^2$. Throughout this consideration, the shadow fading effect is assumed to be quasi-static and the channel gain, $\phi(\mathbf{x}_{su}^m, n)$ is assumed to be time-invariant while SU-c3 is stationary at point 'A' during training and becomes a fading process as it transits from point 'A' at coordinate $\mathbf{x}_{su}^m$ to point 'B' at coordinate $\mathbf{x}_{su}^j$. We further assume that in order to reduce cooperation overhead, although the traveling SU is to be aided by the SBS and other collaborating device within the network, it is primarily responsible for the continuous monitoring of the PU's activities while using the PU's band and would vacate the band immediately when the PU becomes active.

3.1 Energy Vectors Realization for Secondary Users Training

During the training interval, given that the PU operates at a carrier frequency f_c and bandwidth ω, if the transmitted PU signal is sampled at the rate of f_s by each SU, the energy samples sent to the SBS for training purpose can be estimated as [11]

$$\psi_i = \frac{1}{N_s} \sum_{n=1}^{N_s} |x_m(n)|^2 \tag{3}$$

where $n = 1, 2, ..., N_s$ and $N_s = \tau f_s$ is the number of samples of the received PU signal used for computing the training energy sample at the SU while τ is the duration of sensing time for each energy sample realization. When the PU is idle, the probability density function (PDF) of ψ_i follows Chi-square distribution with $2N_s$ degrees of freedom and when N_s is large enough (say, $N_s \simeq 250$) [12], this PDF can be approximated as Gaussian through the central limit theorem with mean, $\mu_0 = \sigma_\eta^2$ and variance, $\sigma_0^2 = \frac{1}{N_s}[\mathbb{E}|\eta(n)|^4 - \sigma_\eta^4]$. However, for an additive white Gaussian noise, $\mathbb{E}|\eta(n)|^4 = 2\sigma_n^4$ so that we have $\sigma_0^2 = \frac{1}{N_s}\sigma_\eta^4$. Similarly, when the PU is active, the distribution of ψ_i can be approximated as Gaussian with mean, $\mu_1 = |\phi(\mathbf{x}_{su}^m, n)|^2\sigma_s^2 + \sigma_\eta^2$ and variance, $\sigma_1^2 = \frac{1}{N_s}[|\phi(\mathbf{x}_{su}^m, n)|^4\mathbb{E}|s(n)|^4 + \mathbb{E}|\eta(n)|^4 - (|\phi(\mathbf{x}_{su}^m, n)|^2\sigma_s^2 - \sigma_\eta^2)^2]$.

Let $\mathbf{\Psi} = \{\psi_1, ..., \psi_{\mathcal{L}}\}$ be the set of training energy vectors obtained at the SBS during the training period where $\psi_l \in R^q$, and q is the dimension of each training energy vector which corresponds to the number of collaborating SUs and antenna per SU. If $\mathbf{\Psi} \in \{H_0, H_1\}$ is fed into the parametric classifier, the output of the classifier is the cluster centroids (means) that can be used to generate the decision boundary which optimally separates the two clusters, H_0, H_1. This decision boundary can then be used for the classification of new data points when the classifier is deployed in an environment similar to where it has been trained given any desired false alarm probability. A simple K-means clustering algorithm for computing the cluster centroids at the SBS is shown in Algorithm 1. However, in the realistic deployment scenario under consideration involving a mobile SU which travels through a fading channel environment where frequent re-training is impractical, relying on the hitherto, optimal decision threshold obtained at the initial point of training would result in detection error. Therefore, in order to achieve high probability of detection and low false alarm, the cluster centroids computed at the SBS have to be continuously updated and the decision boundary adjusted correspondingly.

Algorithm 1. K-means Clustering Algorithm for CR Spectrum Sensing

$\forall\ m = 1, ..., M$, initialize cluster centroids $C_1, ..., C_K$, $\forall\ k = 1, ..., K$ given $\boldsymbol{\Psi}$, K.
do repeat
  for $k \leftarrow 1$ to K
  do $D_k \leftarrow \{\ \}$
  for $l \leftarrow 1$ to $\mathcal{L}$
  do $i \leftarrow argmin_i \|C_i - \psi_l\|^2$
  $D_k \leftarrow D_k \cup \{\psi_l\}$
  do $C_k \leftarrow |D_k|^{-1} \sum_{\psi_l \in D_k} \psi_l, \forall\ k$
until convergence
$C_{H0} \leftarrow min\{|C_1|, ..., |C_K|\}$

3.2 Tracking Decision Boundary Using Kalman Filter Based Channel Estimation

In order to be able to track the changes in the cluster centroids under slow fading channel condition due to the mobility of the SU, we introduce the Kalman filtering technique to enable the mobile SU to obtain an online, unbiased estimate of the temporally correlated fading channel gain. Since the PU is assumed to be alternating between the active and inactive states, a collaborating sensor node (CSN) that is co-locating with the PU is activated during the SU's travel period. The sensor node's duty is to broadcast a signal known to the SUs (e.g. pilot signal) periodically during the PU's idle interval for the benefit of the mobile SUs to enable centroid update and avoid causing harmful interference to the PU's service. The role of the CSN in the proximity of the PU is similar to that of the *helper node* used for authenticating the PU's signal in [13] and the rationale behind incorporating a sensor node co-locating with the PU is to ensure that the channel between the PU and the mobile SU is captured by the CSN-to-mobile SU channel. It should be noted that our model is equally applicable in the case where there are multiple and/or mobile PUs and can accommodate any other collaborating sensor node selection method. The mobile SU on the other hand makes a prediction of the dynamic channel gain based on its speed of travel and combines this prediction with the noisy observation from the collaborating node via the Kalman filtering algorithm to obtain an unbiased estimate of the true channel gain.

Let the discrete-time observation at the mobile SU terminal due to the transmitted signal by the CSN be described by

$$z(t) = s(t)\phi(t) + \varrho(t) \tag{4}$$

where $s(t)$ is a known pilot signal, $\varrho(t)$ is a zero mean complex additive white Gaussian noise at the receiver with variance, σ_ϱ^2 and $\phi(t)$ is a zero mean circularly complex Gaussian channel gain with variance σ_ϕ^2, t is the symbol time index. If we let T_s be the symbol period of the pilot signal, the normalized Doppler frequency of the fading channel is $f_d T_s$ where f_d is the maximum Doppler frequency in Hertz defined by $f_d = \frac{v}{\lambda}$, v is the speed of the mobile and λ is the wavelength of the received signal. The magnitude of the instantaneous channel gain, $|\phi|$ is a random variable whose PDF is described by

$$p_\phi(\phi) = \frac{2\phi}{\nu}\exp(\frac{-\phi^2}{\nu}), \phi \geq 0 \tag{5}$$

where ϕ is the fading amplitude and $\nu = \overline{\phi^2}$ is its mean square value. Furthermore, the phase of $\phi(t)$ is assumed to be uniformly distributed between 0 and 2π. It should be noted, though, that by virtue of the location of CSN in the network, it is assumed that $\phi(t)$ also captures the channel gain between the PU-TX and SU-c3 during every observation interval. For the flat fading Rayleigh channel, the following Jake's Doppler spectrum is often assumed

$$S_\phi(f) = \begin{cases} \frac{1}{\pi f_d\sqrt{1-(f/f_d)^2}}, & |f| \leq f_d \\ 0, & |f| > f_d \end{cases} \tag{6}$$

where f is the frequency shift relative to the carrier frequency. The corresponding autocorrelation coefficient of the observation signal, $z(t)$ under this channel condition is given by [14]

$$\begin{aligned} R_\phi(\epsilon) &= \mathbb{E}[\phi(\kappa)\cdot\phi^*(\kappa-\epsilon)] \\ &= \sigma_\phi^2 J_0(2\pi f_d \epsilon) \end{aligned} \tag{7}$$

for lag ϵ where $J_0(\cdot)$ is the zeroth order Bessel function of the first kind. It should be noted that in the actual deployment for cognitive radio, the idle time of the PU is long enough so that it is possible to periodically obtain the noisy observation (measurement) of the channel gain, $z(t)$ during the PU's idle time [15]. The mobile SU can apply the Kalman filter algorithm described in section 3.3 to obtain an unbiased estimate $\tilde{\phi}$ of the true fading channel gain ϕ which can then be used to update the cluster centroids at the SBS and also for tracking the temporally dynamic optimal decision boundary. Since our target is to use the Kalman filtering to realize the best estimate $\tilde{\phi}$ of ϕ, a prediction of the dynamic evolution of the channel gain is required in addition to the noisy observation $z(t)$. For simplicity, we propose to use a first order autoregressive model ($AR-1$) which has been shown to be sufficient to capture most of the channel tap dynamics in Kalman filter based channel tracking related problems [14]. It should be noted too that the $AR-1$ model is widely acceptable as an approximation to the Rayleigh fading channel with Jake's Doppler spectrum [16], [17]. The $AR-1$ model for approximating the magnitude of time varying complex channel gain can be expressed as

$$\phi_t^{AR-1} = \alpha \cdot \phi_{t-1}^{AR-1} + \zeta(t) \tag{8}$$

where t is the symbol index, $0 < \alpha < 1$ and $\zeta(t)$ is complex additive white Gaussian noise with variance $\sigma_\zeta^2 = (1-\alpha^2)\sigma_\phi^2$. When $\alpha = 1$, the $AR-1$ model for the dynamic evolution of ϕ in (8) becomes a random walk model [14]. One way of obtaining the coefficient of the $AR-1$ model, α expressed as

$$\alpha = \frac{R_\phi^{AR-1}[1]}{R_\phi^{AR-1}[0]} \tag{9}$$

is by using correlation matching criterion whereby the autocorrelation function of the temporally correlated fading channel is matched with the autocorrelation function of the approximating AR model for lags 0 and 1 such that $R_\phi^{AR-1}[0] = R_\phi[0]$ and $R_\phi^{AR-1}[1] = R_\phi[1]$. However, if the evolution of the dynamic channel gain is modeled by a higher order AR process, the required coefficients can be obtained by solving the Yule-Walker set of equations [17].

Remarks: The optimal estimate of the channel gain that is obtained via the Kalman filter is sufficient to enable the mobile SU avoid frequent and total dependence on the CSN or other SUs for information regarding the status of PU-TX and the associated overhead.

3.3 Kalman Filtering Channel Estimation Process

At this point having obtained α, we combine the observation equation (4) and state evolution equation (8) to form a Kalman filter set of equations as [18]

$$\hat{\phi}_{t|t-1} = \alpha\hat{\phi}_{t-1|t-1} \tag{10}$$

$$M_{t|t-1} = \alpha^2 M_{t-1|t-1} + \sigma_\zeta^2 \tag{11}$$

$$K_t = \frac{M_{t|t-1}}{M_{t|t-1} + \sigma_\varrho^2} \tag{12}$$

$$\hat{\phi}_{t|t} = \hat{\phi}_{t|t-1} + K_t(z(t) - \alpha\hat{\phi}_{t|t-1}) \tag{13}$$

$$M_{t|t} = (1 - K_t)M_{t|t-1} \tag{14}$$

where K_t is the Kalman gain , $M_{t|t}$ is the variance of the prediction error and $\hat{\phi}_{t|t}$ is the desired optimal estimate of ϕ_t. It is pertinent to mention here that in the rare event that the PU is active for an unexpectedly prolonged period of time so that it becomes impossible to obtain an observation, the situation can be treated as missing observation. Suppose this occurs at a time t, the Kalman filtering prediction step described by (10) and (11) remains the same while the correction step in (13) and (14) will become

$$\hat{\phi}_{t|t} = \hat{\phi}_{t|t-1} \tag{15}$$

$$M_{t|t} = M_{t|t-1} \tag{16}$$

and if the period of missing observation is extremely prolonged, the significance on the detection of PU status is that the mobile SU loses its ability to track the fading channel for that period so that the only effect taken into consideration is the path loss. Consequently, it could be seen that even under this situation the proposed scheme does not perform worse than the alternative where the channel tracking is not considered (path loss only model). A simple algorithm for implementing the proposed enhanced classifier is presented in Algorithm 2.

Algorithm 2. Kalman Filter Enhanced Parametric Classifier based Spectrum Sensing Algorithm

1. Generate cluster centroids, $C_k \; \forall \; k = 1, ..., K$ at the SBS using Algorithm 1.
2. Initialize parameters α, $M_{t-1|t-1}$ and σ_ζ^2 at the SUs.
3. **if** SU begins motion, $t \leftarrow 1$
4. **repeat**
5. SU obtains $z(t)$ in (4) during PU's idle interval and computes $\hat{\phi}_{t|t}$ and $M_{t|t}$ using (10) - (14).
6. Compute new energy samples at SU using $\hat{\phi}_{t|t}$ in step 5 and update cluster centroids at the SBS.
7. Use updated centroids from step 6 to decide the PU status, H_0 or H_1.
8. $t \leftarrow t + 1$
9. **until** SU ends motion
10. **end if**

4 Simulation Results and Discussion

For simulation purpose, the average power of the fading process is normalized to unity and the mobile SU under consideration (SU-c3) is assumed to be equipped with an omnidirectional antenna while traveling at a constant velocity of 6 km/hr. We considered a single PU which operates alternately in the active and inactive modes, so that the number of clusters, K is 2. The symbol frequency of the PU is 10 ksymbol/s transmitted at the central carrier frequency of 1.8 GHz. As the SU travels, to model the effects of the scatterers, we assume that a total of 128 equal strength rays at uniformly distributed angles of arrival impinge on the receiving antenna, so we have a normalized Doppler frequency of 1e-3. During training the path loss exponent, d is assumed equals to 3 while the shadow

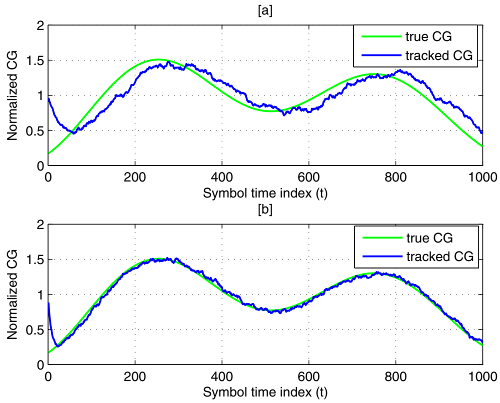

Fig. 2. Time varying channel gain (CG) tracked at [a] $SNR = 5\ dB$ and [b] $SNR = 20\ dB$.

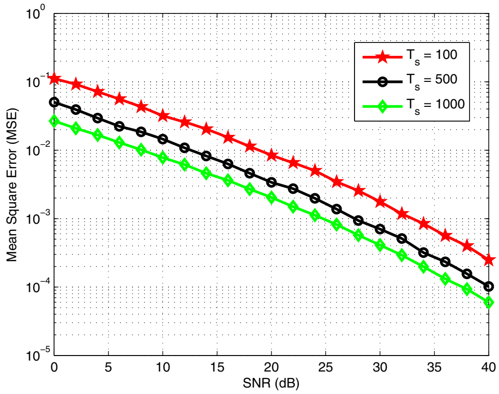

Fig. 3. Mean square error performance of the AR-1 based Kalman filter at normalized Doppler frequency = 1e-3, tracking duration, T_s = 100, 500 and 1000 symbols.

fading component $\delta_{\mathbf{x}_{pu} \rightarrow \mathbf{x}_{su}^m}$ and the small scale fading factor, $\gamma_{\mathbf{x}_{pu} \rightarrow \mathbf{x}_{su}^m}$ are both assumed equal to 1, the PU signal is BPSK and transmit power is 1 Watt. The training energy samples at the SUs are computed using $N_s = 1000$. When SU is in motion, the waveform of the temporally correlated Rayleigh fading process to be tracked is generated using the modified Jake's model described in [19]. To test the enhanced classifier, we assume the mobile SU-c3's trajectory is at an approximately constant average distance to PU-TX throughout the duration of travel and energy samples for updating the centroids are computed using $N_s = 1000$.

In Fig. 2, we show the ability of the Kalman filter in tracking the true channel gain when the pilot signals are received from the CSN at SNR of 5 dB and 20

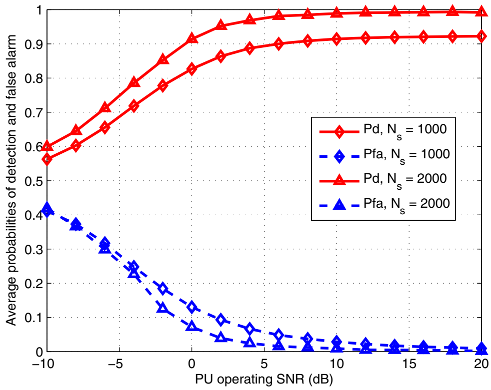

Fig. 4. Average probabilities of detection and false alarm vs SNR, tracking $SNR = 5$ dB, number of samples, $N_s = 1000$ and 2000, tracking duration = 1000 symbols.

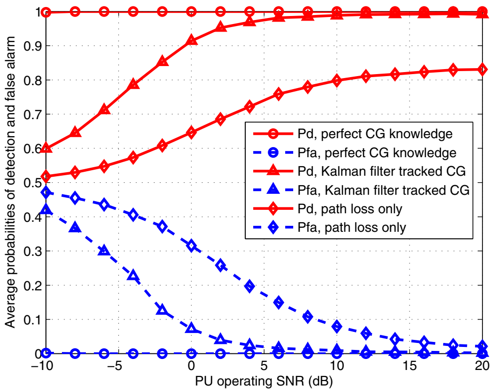

Fig. 5. Average probabilities of detection and false alarm vs SNR, tracking $SNR = 5$ dB, number of samples, $N_s = 2000$, tracking duration = 1000 symbols.

dB respectively over an observation window of 1000 symbol duration. It could be seen that as the pilot's SNR is increased, the performance of the tracker also improves. The mean square error performance of the AR-1 based Kalman filter is shown in Fig. 3 at normalized Doppler frequency of 1e-3 where at the same SNR the tracking error reduces for different duration of tracked pilot symbols (tracking duration). This shows that the longer the tracking duration the better the overall performance of the tracker. It is also seen that the average error reduces from 5e-2 to 16e-5 with increase in tracking SNR from 0 dB to 40 dB when the tracking duration, $T_s = 1000$. The effect of the number of PU's signal samples, N_s used for computing the energy features for training, tracking and testing on the average probabilities of detection (Pd_{Av}) and false alarm (Pfa_{Av})

is shown in Fig. 4. Here, a considerable improvement in Pd_{Av} is observed as N_s is increased from 1000 to 2000.

In Fig. 5, we show the performance of the enhanced classifier in terms of Pd_{Av} and Pfa_{Av} and compared this with the path loss only model. Here, the pilot symbols from the CSN are assumed to be received at the SNR of 5 dB each time the decision boundary is updated. When the PU's signal is received at SNR of 20 dB, it could be seen that the enhanced classifier attains Pd_{Av} of unity at zero Pfa_{Av} while at PU's operating SNR of 0 dB, Pd_{Av} of about 0.91 is achieved at Pfa_{Av} equals 0.07 in spite of the degradation in sensing path. This is in contrast to what obtains from the path loss only model where at the SNR of 20 dB, Pd_{Av} is only about 0.83 at a non-zero Pfa_{Av}. In summary, a performance improvement of about 20 percent is observable in the enhanced scheme with only very slight increase in overall system's complexity.

5 Conclusion

In this paper, we investigated the use of parametric classifiers in cognitive radio network for spectrum sensing purpose under slowly varying flat fading conditions involving mobile secondary users and proposed a novel Kalman filter based channel estimation technique to enhance their performance. Simulation results show that by utilizing few collaborating secondary devices, the average correct detection probability of about 90% can be achieved at 0 dB given 2000 samples of the PU signal, while keeping the average false alarm probability below 10%. In the future, we intend to extend this work to the detection of spatial spectrum hole while considering other realistic cognitive radio deployment scenarios.

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References

1. Haykin, S.: Cognitive Radio: Brain-empowered Wireless Communications. IEEE J. Sel. Areas Commun. **23**(2), 201–220 (2005)
2. Akyildiz, I.F., Lo, B.F., Balakrishnan, R.: Cooperative Spectrum Sensing in Cognitive Radio Networks: A Survey. Phys. Commun. J. **4**(1), 40–62 (2011)
3. Yucek, T., Huseyin, A.: A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications. IEEE Commun. Surv. Tut. **11**(1), 116–130 (2009)
4. Awe, O.P., Zhu, Z., Lambotharan, S.: Eigenvalue and support vector machine techniques for spectrum sensing in cognitive radio networks. In: Conf. Technol. Appl. Artif. Intell., Taipei, Taiwan, pp. 223–227 (2013)
5. Thilina, K., Saquib, N., Hossain, E.: Machine Learning Techniques for Cooperative Spectrum Sensing in Cognitive Radio Networks. IEEE J. Sel. Areas Commun. **31**(11), 2209–2221 (2013)
6. Awe, O.P., Naqvi, S.M., Lambotharan, S.: Variational bayesian learning technique for spectrum sensing in cognitive radio networks. In: 2nd IEEE Glob. Conf. Signal Inf. Process., Atlanta, GA, USA, pp. 1353–1357 (2014)

7. Bkassiny, M., Li, Y., Jayaweera, S.K.: A Survey on Machine Learning Techniques in Cognitive Radios. IEEE Commun. Surv. Tut. **15**(3), 1136–1159 (2013)
8. Biao, C., Ruixiang, J., Kasetkasem, T., Varshney, P.K.: Fusion of decisions transmitted over fading channels in wireless sensor networks. In: Conf. Rec. Thirty-Sixth Asilomar Conf. Signals, Syst. Comput., Pacific Grove, CA, USA, pp. 1184–1188 (2002)
9. Wang, T., Song, L., Han, Z., Saad, W.: Overlapping coalitional games for collaborative sensing in cognitive radio networks. In: IEEE Wirel. Commun. Netw. Conf., Shanghai, China, pp. 4118–4123 (2013)
10. Kondareddy, Y., Agrawal, P.: Enforcing cooperative spectrum sensing in cognitive radio networks. In: IEEE Glob. Tel. Conf., Houston, USA, pp. 1–6 (2011)
11. Liang, Y., Zeng, Y.: Sensing-Throughput Tradeoff for Cognitive Radio Networks. IEEE Trans. Wirel. Commun. **7**(4), 1326–1337 (2008)
12. Urkowitz, H.: Energy Detection of Unknown Deterministic Signals. Proc. IEEE **55**(4), 523–531 (1967)
13. Liu, Y., Ning, P., Dai, H.: Authenticating primary users' signals in cognitive radio networks via integrated cryptographic and wireless link signatures. In: IEEE Symp. Secur. Priv., Oakland, CA, USA, pp. 286–301 (2010)
14. Gerzaguet, R., Ros, L.: Self-adaptive stochastic rayleigh flat fading channel estimation. In: 18th Int. Conf. Digit. Signal Process., Fira, Greece, pp. 1–6 (2013)
15. Kim, S.J., DallAnese, E., Giannakis, G.B.: Cooperative Spectrum Sensing for Cognitive Radios Using Kriged Kalman Filtering. IEEE J. Sel. Top. Signal Process. **5**(1), 24–36 (2011)
16. Ros, L., Simon, E.P., Shu, H.: Third-order Complex Amplitudes Tracking Loop for Slow Flat Fading Channel Online Estimation. IET Commun. J. **8**, 360–371 (2014)
17. Baddour, K.E., Beaulieu, N.C.: Autoregressive Modeling for Fading Channel Simulation. IEEE Trans. Wirel. Commun. **4**(4), 1650–1662 (2005)
18. Kay, S.M.: Fundamentals of Statistical Signal Processing, Vol. II: Detection Theory.Signal Process, Up. Saddle River, NJ Prentice (1998)
19. Dent, P., Bottomley, G.E., Croft, T.: Jakes Fading Model Revisited. Electron. Lett. **29**(13), 1162–1163 (1993)