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Analysing Primary Signal Sensing Test in Cognitive Radio Networks Using an Alpha-Beta Filter and a Neyman-Pearson Detector

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Abstract: The signal strength sensing in the context of cognitive radio networks (CRNs), is very important to predict the primary signal of base station (PBS), particularly when the secondary user (SU) is in a congested environment, and also when is in motion towards the end of coverage of PBS. However, this article presents an analysis on the prediction of primary signal strength in CRNs using an Alpha-Beta Filter (ABF) and a Neyman-Pearson Detector (NPD). The challenge of this contribution is based on a realistic sensing of primary signal strength and to do that, we have assumed that the reporting channels between the SU and the PBS are composited with the shadowing and multipath fading (SMF), and the receiver noise has also added. In this regard, the obtained results were discussed through: the signal-to-noise ratio (SNR) uncertainty, the detection probability (PD) and the False Alarm Probability (PFA), where the average relative error of prediction for the PD will be equal to 10^{-5}.

Keywords: Alpha-Beta Filter, Neyman–Pearson Detector, Kalman filter, Energy Detector.

1. INTRODUCTION

Today, the bandwidth of radio spectrum has become very limited due to the increased availability of wireless networks technologies, such as: Wireless Local Area Network (WLAN), Worldwide Interoperability for Microwave Access (WiMax), Universal Mobile Telecommunications System (UMTS), Long-Term Evolution (LTE) and so on. The enhancement of licensed spectrum utilization is very important for the future generation wireless networks in order to satisfy the increasing demand, in terms of transmission capacity, wireless network coverage area, quality of service and so on. Nevertheless, after more than ten years of research, the suggestion to use the cognitive radio (CR) technology introduces a remarkable solution and also leads to obtain the optimum results for the wireless networks [1-3].

The CR technology has been considered as a next generation wireless communication, it able to observe the radio spectrum under a wide bandwidth. Additionally, it can be used to spot the presence or absence of a primary signal under a licensed frequency band, and it employs the same frequency band, but without interfering with the primary users. The CR has been aroused much interest throughout the modern telecommunications. It is expected to be a promising solution and cost-effective for the next generation wireless networks (5G) [2,3].

Spectrum sensing [3] is a key way that will enhance the awareness of spectrum in the CRNs. In realistic, the sensing performance can be deteriorated in a congested environment, where both the sensing and reporting channels between the SU and the PBS are composited with the shadowing and multipath fading. In these conditions, the detection can be achieved regimes where the energy level of the received signal at the SU is below the threshold energy detection in the CRNs, this can be conducted to missed detection probability [4,5].

In this article, the predicted sensing performance of the primary signals in the CRNs using an ABF [6] and a NPD [4], is investigated in a real scenario. The analysis is based on a congested environment [7], where the SU is moving all along with a random Waypoint pattern and it senses the received primary signals from the PBS. To summarize, the important points of our contribution are as follows:

- The first stage has a test about the mobility impact of the SU on the sensing performance of a primary signal. However, during this stage, the positions and velocities of the SU were predicted by using an ABF we have also proposed to use the random Waypoint as a mobility model.

- The second stage has an analysis about the shadowing and multipath fading effects on the sensing performance of the primary signals in CRNs. So, in these conditions, we must to get a signal strength measure at the SU, as well as the signal-to-noise ratio (SNR) uncertainty for each link distance between the SU node and the PBS node. To do that, the log-normal shadowing model has been used.
- The NPD has been used in the third stage. The prediction of the primary signal was evaluated using two metrics, which are known as the Detection Probability (PD) and the False Alarm Probability (PFA). The PFA was set at 0.01, 0.001 and 0.0001.

In this paper, we use a novel algorithm to predict a primary signal (see Fig. 1), in contrast to the scheme that has been investigated in [8]. To validate this contribution, we proposed to compare the two approaches via the optimal prediction of the average relative error.

The rest of this article is organized as follows: Section 2 presents some preliminaries and proposed method, and Section 3 gives the simulation results with the interpretations. Finally, the paper is concluding in Section 4.

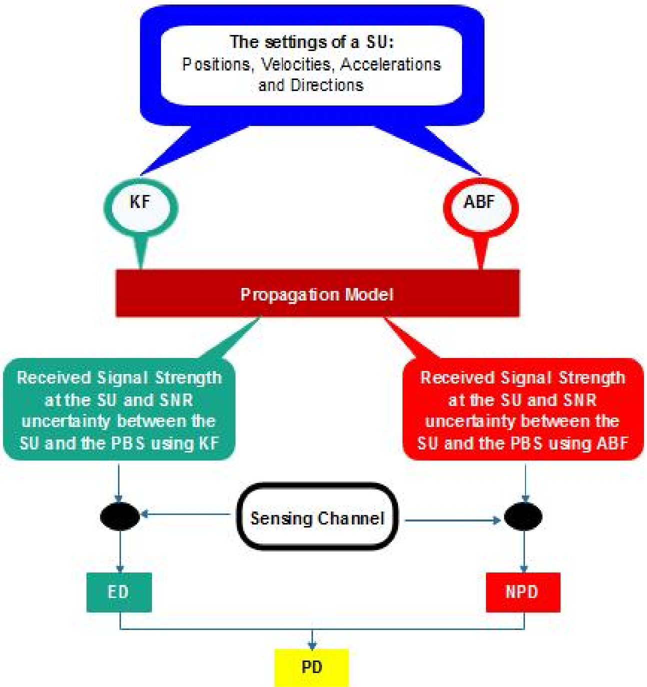


Fig. 1 Proposed algorithm.

2. PROPOSED METHOD

An overview of the CRN architecture is shown in Fig. 2. The proposed situation of CRN architecture consists of the primary base station (PBS) and the secondary user (SU), where, the PBS is found at position (0,0) and the SU is located at (x_i, y_j), is taking the random direction using the random Waypoint model [9].

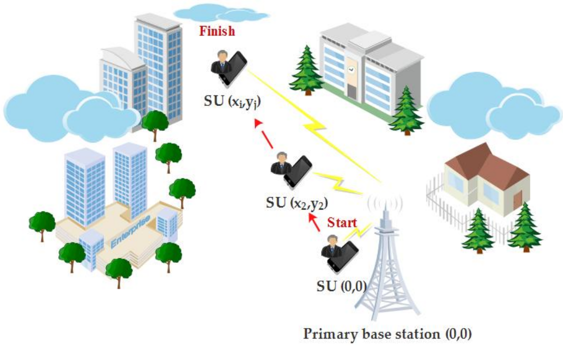


Fig. 2 CRN model.

In addition, the proposed algorithm is modeled with mathematical equations and can be explained with the help of Fig. 1.

The methodology of proposed algorithm can be explained with the following three main steps:

- Alpha-beta tracking filter;
- SNR uncertainty;
- Sensing techniques.

Alpha-Beta Tracking Filter

In this section, we summarize the overall performance of ABF that will be intended to use in the proposed contribution.

An ABF is a simple recursive estimator, it has many uses, including applications in automatic systems, control theory, data smoothing, signal processing, navigation systems and wireless networks...One of main advantages is that it does not include the process noise. In addition, an ABF predicts the position, velocity of a moving node (here the SU node) based on a constant acceleration model using two filter gains, such as alpha (α) and beta (β). This filter uses two-steps, known as: the prediction and smoothing processes [6,10].

First stage - The prediction process may be formulated by the following equations [10]

$$\text{Axis x}\left|\begin{aligned} x_p(i) &= x_s(i-1) + T\,v_{xs}(i-1) + \left(\frac{T^2}{2}\right) a_s(i-1) \\ v_{xp}(i) &= v_{xs}(i-1) + T\,a_s(i-1) \end{aligned}\right. \quad (1)$$

$$\text{Axis y}\left|\begin{aligned} y_p(j) &= y_s(j-1) + T\,v_{ys}(j-1) + \left(\frac{T^2}{2}\right) a_s(j-1) \\ v_{yp}(j) &= v_{ys}(j-1) + T\,a_s(j-1) \end{aligned}\right. \quad (2)$$

Where T is the sampling interval or the time step, $(x(i), y(j))$ is the position, $(v_x(i), v_y(j))$ is the velocity, $(a(i),\ a(j))$ is the acceleration, notations p and s indicate the predicted and smoothed state values, respectively.

The equations (1) and (2) can be written by the following state equations [10]

$$\left|\begin{aligned} x_p(i) &= x_s(i-1) + T\,v_{xs}(i-1) + \left(\frac{T^2}{2}\right) a_s(i-1) \\ y_p(j) &= y_s(j-1) + T\,v_{ys}(j-1) + \left(\frac{T^2}{2}\right) a_s(j-1) \\ v_{xp}(i) &= v_{xs}(i-1) + T\,a_s(i-1) \\ v_{yp}(j) &= v_{ys}(j-1) + T\,a_s(j-1) \end{aligned}\right. \quad (3)$$

So, one can get the evolution of this system in a matrix manner, as expressed by the following equations [10]

$$X_p(k) = \begin{bmatrix} x_p(i) \\ y_p(j) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_s(i-1) \\ y_s(j-1) \end{bmatrix} + \begin{bmatrix} T & 0 \\ 0 & T \end{bmatrix} \begin{bmatrix} v_{xs}(i-1) \\ v_{ys}(j-1) \end{bmatrix} + \begin{bmatrix} T^2/2 & 0 \\ 0 & T^2/2 \end{bmatrix} * \begin{bmatrix} a_s(i-1) \\ a_s(j-1) \end{bmatrix}$$

$$X_p(k) = \Phi X_s(k-1) + H\,V_s(k-1) + \Gamma\,a_s(k-1) \quad (4)$$

And

$$V_p(k) = \begin{bmatrix} v_{xp}(i) \\ v_{yp}(j) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_{xs}(i-1) \\ v_{ys}(j-1) \end{bmatrix} + \begin{bmatrix} T & 0 \\ 0 & T \end{bmatrix} * \begin{bmatrix} a_s(i-1) \\ a_s(j-1) \end{bmatrix} = \Lambda V_s(k-1) + \Psi\, a_s(k-1) \quad (5)$$

Second stage - The settings are computed with the previously predicted values and the smoothing process is expressed as follows [10]

$$X_s(k) = X_p(k) + \alpha\,(X_0(k) - X_p(k)) \quad (6)$$

$$V_s(k) = V_p(k) + \left(\frac{\beta}{T}\right)(X_0(k) - X_p(k)) \quad (7)$$

Where $X_0(k)$ is the actual position.

The following equation illustrates the condition used for practical gains α, β when using an alpha-beta filter.

$$0 < \alpha < 1, 0 < \beta < 1 \quad (8)$$

The next section focuses on describing the SNR uncertainty.

SNR uncertainty

In this section, the SNR uncertainty at each link between the PBS and the SU can be estimated. However, the estimation of a SNR uncertainty is carried out according to the following steps:

– The distance estimate:

The distance estimate between two nodes the PBS and the SU is calculated. Note that in order to evaluate the distance estimate between two nodes, we know that the relationship of Euclidean distance can be used. It can be expressed by [8,11]

$$\hat{d} = \sqrt{\left(x_{i\,(PU)} - \hat{x}_{i\,(SU)}\right)^2 + \left(y_{j\,(PU)} - \hat{y}_{j(SU)}\right)^2} \quad (9)$$

Where the ABF provides the first position estimate of secondary user $\left(\hat{x}_{i\,(SU)}, \hat{y}_{j\,(SU)}\right)$, and also the distance estimate between two nodes the PBS and the SU.

– The $\hat{P}_{RSS}$ estimate:

The received signal strength ($\hat{P}_{RSS}$) at the SU in dB, from sender node (PBS) to receiver node (SU) is estimated and calculated. It is given by the following equation (10) [8,11]

$$\hat{P}_{RSS(SU)}(\hat{d}) = P_{tx(PU)} - PL(\hat{d}) \quad (10)$$

Where

$$PL(\hat{d}) = 20\log_{10}\left(\frac{4\pi d_0}{\lambda}\right) + 10\mu\log_{10}\left(\frac{\hat{d}}{d_0}\right) \quad (11)$$

The log-distance path loss model can be obtained from the equation (10). It is expressed by the following equation (12)

$$\hat{P}_{RSS(SU)}(\hat{d}) = P_{RSS(SU)}(d_0) - 10\mu\log_{10}\left(\frac{\hat{d}}{d_0}\right) \quad (12)$$

Where

$$P_{RSS(SU)}(d_0) = P_{tx(PU)} - 20\log_{10}\left(\frac{4\pi d_0}{\lambda}\right) \quad (13)$$

In addition, the log-normal shadowing model is that easy to get, an additional element X_σ is added in the log-distance path loss model. This model may be expressed by the following equation (14)

$$\hat{P}_{RSS(SU)}(\hat{d}) = P_{RSS(SU)}(d_0) - 10\mu\log_{10}\left(\frac{\hat{d}}{d_0}\right) + X_\sigma \quad (14)$$

Where $\hat{P}_{RSS(SU)}$ is the received signal strength estimate at the SU in dB, $P_{tx(PU)}$ is the transmit power by the PBS in dB, $PL(\hat{d})$ is the path-loss at a distance $\hat{d}$ in dB, $\hat{d}$ is the estimated distance between the PBS and the SU, λ is the wavelength of the signal, μ is the path-loss exponent, d_0 is a reference distance and X_σ is zero-mean, complex, Gaussian random processes and with a standard deviation σ.

– The SNR uncertainty estimate:

To each link distance between two nodes the PBS and the SU, the SNR uncertainty is estimated and calculated. It is expressed by the following general equation (15) [8,11]

$$\widehat{\mathrm{SNR}}_{(\mathrm{PU,SU})}(\mathrm{dB}) = 10\log_{10}\left(\frac{\hat{P}_{RSS(SU)}(\hat{d})}{P_{Noise}}\right) \quad (15)$$

Where P_{Noise} is a noise power.

The objective of the next section is to predict the probability of total detection error, from the previous steps.

Sensing techniques

The objective of this section is to estimate the detection probability (PD), from the previous steps. The performance of sensing technique used in this paper is described by a simple local sensing model. However, the policy is performed based on detecting the energy levels of the received signal estimate at the SU. It can be formulate by a binary hypothesis testing, as follows [4,7]

$$\begin{cases} \hat{S}_{Rx}(t) = u(t)\,;\ \{H_0\} \\ \hat{S}_{Rx}(t) = S_{Tx}(t) + u(t)\,;\{H_1\} \end{cases} \quad (16)$$

Where $\hat{S}_{Rx}(t)$ is the received signal estimate at the SU, $S_{Tx}(t)$ is the transmitted signal by the PBS and $u(t)$ is the noise effect (here $u(t)$ is an additive white Gaussian noise (AWGN)). The hypothesis of the presence and absence of the PBS are H_1 and H_0, respectively. The decision whether the primary signal is present or absent by measuring the energy level of the received signal estimate at the SU, $\hat{E}$, it was compared with the energy detection threshold, θ, namely:

$$\begin{cases} H_1: \hat{E} = \left(\frac{1}{M}\right)\sum_{n=1}^{M}\left|\hat{S}_{Rx}(n)\right|^2 > \theta \\ H_0: \hat{E} = \left(\frac{1}{M}\right)\sum_{n=1}^{M}\left|\hat{S}_{Rx}(n)\right|^2 < \theta \end{cases} \quad (17)$$

Where θ is the energy detection threshold and M is the number of samples taken for sensing.

To evaluate the sensing performance, two parameters are used, namely the detection probability (PD), and false alarm probability (PFA) which are given by the equations (18) and (19), respectively [4,7]

$$PD = P_r\{\hat{E} > \theta, H_1\} \quad (18)$$

$$PFA = P_r\{\hat{E} > \theta, H_0\} \quad (19)$$

In this paper, the SU is assumed to be equipped with a NPD.

The NPD shows that the signal of the PBS is present if the likelihood ratio exceeds a certain threshold, as expressed in [4,7]

$$Y(\hat{E}) = \frac{P_r\{\hat{E}>\theta, H_1\}}{P_r\{\hat{E}>\theta, H_0\}} > \theta \quad (20)$$

Therefore,

$$P_r\{\hat{E} > \theta, H_1\} = \frac{1}{(2\pi\sigma_0^2)^{\frac{M}{2}}}\ \exp\left[-\frac{1}{2\sigma_0^2}\ \sum_{n=0}^{M-1}\left(\hat{S}_{Rx}[n] - S_{Tx}[n]\right)^2\right] \quad (21)$$

$$P_r\{\hat{E} > \theta, H_0\} = \frac{1}{(2\pi\sigma_0^2)^{\frac{M}{2}}}\ \exp\left[-\frac{1}{2\sigma_0^2}\ \sum_{n=0}^{M-1}\hat{S}_{Rx}{}^2[n]\right] \quad (22)$$

Using equations (21) and (22), equation (20) can be expressed again as follows [4,7]

$$Y(\hat{E}) = Z > \theta \quad (23)$$

Where

$$Z = \exp\left[-\frac{1}{2\sigma_0^2}\left(\sum_{n=0}^{M-1}\left(\hat{S}_{Rx}[n] - S_{Tx}[n]\right)^2 - \sum_{n=0}^{M-1}\hat{S}_{Rx}{}^2[n]\right)\right]$$

The equation (23) can be simplified, if we take logarithm of both sides, without changing the inequality

$$-\frac{1}{2\sigma_0^2}\left(\sum_{n=0}^{M-1}\left(\hat{S}_{Rx}[n] - S_{Tx}[n]\right)^2 - \sum_{n=0}^{M-1}\hat{S}_{Rx}{}^2[n]\right) > \ln(\theta) \quad (24)$$

Also, it can be stated that the PBS is present if

$$\frac{1}{\sigma_0^2}\sum_{n=0}^{M-1}\hat{S}_{Rx}[n]S_{Tx}[n]-\frac{1}{2\sigma_0^2}\sum_{n=0}^{M-1}{S_{Tx}}^2[n]>\ln(\theta) \quad (25)$$

The energy level of the primary signal may be integrated into the energy detection threshold

$$Y'(\hat{E})=\sum_{n=0}^{M-1}\hat{S}_{Rx}[n]S_{Tx}[n]>\sigma_0^2\ln(\theta)+\frac{1}{2}\sum_{n=0}^{M-1}{S_{Tx}}^2[n] \quad (26)$$

If we considered a new energy detection threshold, θ′, the equation (26) can be simplified by the following equation

$$Y'(\hat{E})=\sum_{n=0}^{M-1}\hat{S}_{Rx}[n]S_{Tx}[n]>\theta' \quad (27)$$

Where

$$\theta'=\sigma_0^2\ln(\theta)+\frac{1}{2}\sum_{n=0}^{M-1}{S_{Tx}}^2[n] \quad (28)$$

$Y'(\hat{E})$ is a linear combination of Gaussian random variables and it is as well as Gaussian.

To sense whether the PBS is present (H_1) or absent (H_0), the replica-correlator was used. Besides, the expected value $E(Y';H_k)$ and the variance $var(Y';H_k)$ of $Y'(\hat{E})$ under H_k are presented as follows [4,7]

$$E(Y';H_0)=E\left(\sum_{n=0}^{M-1}u[n]S_{Tx}[n]\right)=0 \quad (29)$$

$$E(Y';H_1)=E\left(\sum_{n=0}^{M-1}(u[n]+S_{Tx}[n])\,S_{Tx}[n]\right)=\hat{\varepsilon} \quad (30)$$

$$var(Y';H_0)=var\left(\sum_{n=0}^{M-1}u[n]S_{Tx}[n]\right)$$

$$var(Y';H_0)=\sum_{n=0}^{M-1}var(u[n]){S_{Tx}}^2[n]$$

$$var(Y';H_0)=\sigma_0^2\sum_{n=0}^{M-1}{S_{Tx}}^2[n]=\sigma_0^2\hat{\varepsilon} \quad (31)$$

When the factors of u[n] are uncorrelated, then the $var(Y';H_1)$ is equal to $\sigma_0^2\hat{\varepsilon}$.

Thereby, the test statistic Y' is a normal distribution law, under the assumption H_1. This law is not centered, while it is under H_0, as expressed in the equation

$$Y'\sim\begin{cases}H_1:\mathcal{N}(\hat{\varepsilon},\ \sigma_0^2\hat{\varepsilon})\\ H_0:\mathcal{N}(0,\ \sigma_0^2\hat{\varepsilon})\end{cases} \quad (32)$$

Based on the equation (32), one can get the PFA as well as the PD as follows

$$PFA=P_r(Y'>\theta';H_0)=Q\left(\frac{\theta'}{\sqrt{\sigma_0^2\hat{\varepsilon}}}\right) \quad (33)$$

$$PD=P_r(Y'>\theta';H_1)=Q\left(\frac{\theta'-\hat{\varepsilon}}{\sqrt{\sigma_0^2\hat{\varepsilon}}}\right) \quad (34)$$

The equation (25) can be written otherwise using the inverse function $Q^{-1}(.)$ as

$$\theta'=\sqrt{\sigma_0^2\hat{\varepsilon}}\ Q^{-1}(PFA) \quad (35)$$

Substituting equation (35) into (34), yields another expression

$$PD=Q\left(\frac{\sqrt{\sigma_0^2\hat{\varepsilon}}\ Q^{-1}(PFA)-\hat{\varepsilon}}{\sqrt{\sigma_0^2\hat{\varepsilon}}}\right)=Q\left(Q^{-1}(PFA)-\sqrt{\frac{\hat{\varepsilon}}{\sigma_0^2}}\right) \quad (36)$$

With $\hat{\varepsilon}$ is the energy level of the received signal estimate at the SU, σ_0^2 is the noise power, $\frac{\hat{\varepsilon}}{\sigma_0^2}$ is the SNR uncertainty estimate and $Q^{-1}(.)$ is the generalized Marcum Q - inverse function [12-15].

3. SIMULATION RESULTS AND DISCUSSION

In this section, we introduce the derived simulation and analytical results that were obtained in our study. In this contribution, we are interested in predicting the probability of the primary signal sensing by the SU in a real-time, i.e., in a congested environment and also the SU node was considered in motion. The table 1 set the simulation parameters [7,8].

The discussion in the first stage of the proposed algorithm was carried to predict the position and velocity of the SU compared to a benchmark that was the PBS.

Table 1 Simulation parameters

Simulation area	214 x 214 [m^2]
Transmission frequency	2.45 (GHz)
Transmit power: $P_{tx(PU)}$	25 (dBm)
Sensing level	-85.0 (dBm)
Noise power: P_{Noise}	-95.0 (dBm)
Path loss exponent: μ	3.0
Reference distance: d_0	1.0 (m)
α and β	0.995 and 0.0004

Fig. 3 below illustrates the position-tracking of the SU node within 35 s. It can clearly be seen that the position-tracking using the ABF provides the best results versus the KF. As a general remark, it was observed from the relative error of a position (see Fig. 4), we have perceived that at low value of a relative error of a position is obtained with the ABF, where the average relative error of a position is approximately equal to $2.96 * 10^{-2}$ m. In contrast to the KF [8], the average relative error of a position is approximately equal to $9.825 * 10^{-1}$ m.

The velocity of the SU is another major factor, which can be deteriorated the sensing performance of the primary signal. So, the Fig. 5 below illustrates the velocity-tracking of the SU node within 35 s. According to the trajectory of the real and estimated velocity of the SU using the ABF and the KF, we can clearly see that the velocity is increased, as well as sometimes it is decreased. It was also observed that at low value of the relative error of a velocity was provided through an ABF, but not with the KF (see Fig. 6). For this note, the average relative error of a velocity with the ABF is approximately equal to $2.4 * 10^{-3}$ m/s, In contrast with the KF [8], the average relative error of a velocity is approximately equal to $8.66 * 10^{-2}$ m/s.

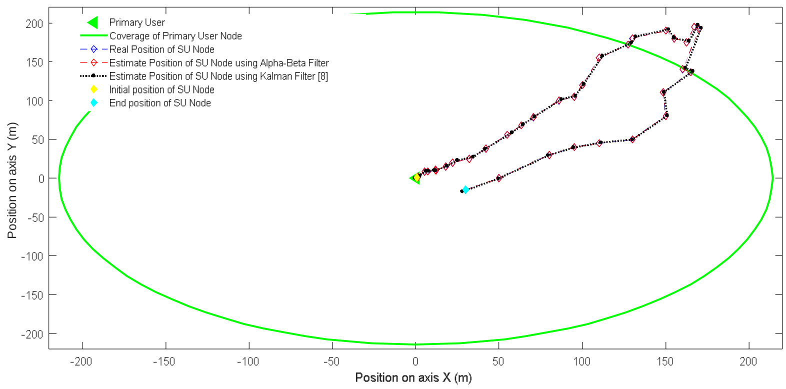


Fig. 3 Position of a SU versus time (s).

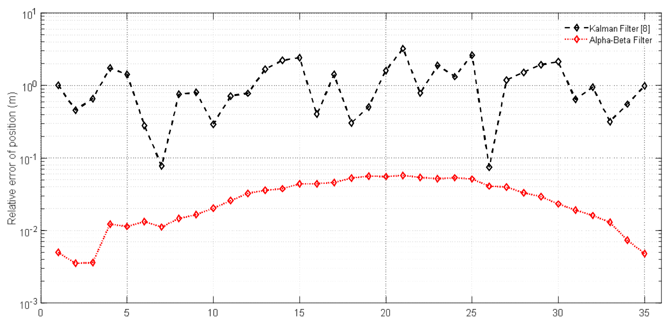


Fig. 4 Relative error of a position (m) versus time (s).

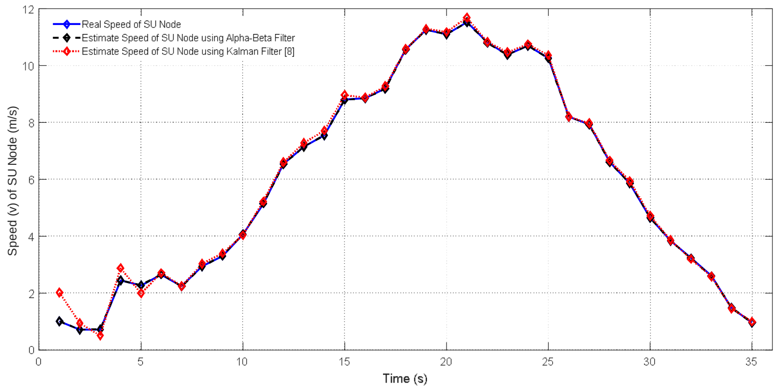


Fig. 5 Velocity of a SU versus time (s).

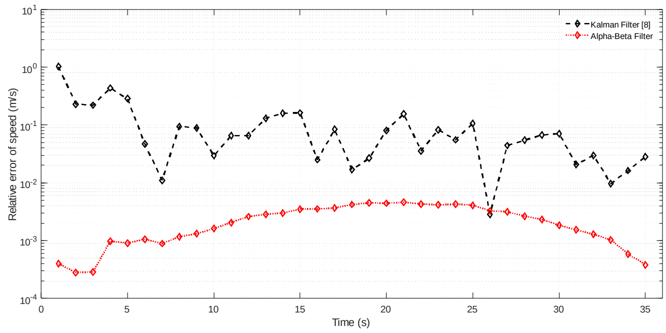


Fig. 6 Relative error of a velocity (m/s) versus time (s).

In the second stage of the proposed algorithm, the estimated of the SNR uncertainty requires with the following information: the distance between the SU and the PBS, the received signal strength at the SU and the noise power at the receiver. All these information are obtained from the previous results.

To study the impact of the position and velocity of the SU on the SNR uncertainty between the SU and the PBS, we plot in Fig. 7 the real and estimated SNR uncertainty between the SU and the PBS, using the ABF and the KF. As anticipated, when the SU is located away from the center of the PBS, near the perimeter of the coverage, the SNR uncertainty is decreased and vice versa. In addition, higher velocity of the SU (see Fig. 5) leads to bad form of the SNR uncertainty between the SU and the PBS. Finally, we have noticed that the average relative error of the SNR uncertainty with the ABF is in excellent, and it is approximately equal to $7.7 * 10^{-3}$dB. And compared it with the KF, the average relative error of the SNR uncertainty is approximately equal to $7.583 * 10^{-1}$ dB (see Fig. 8).

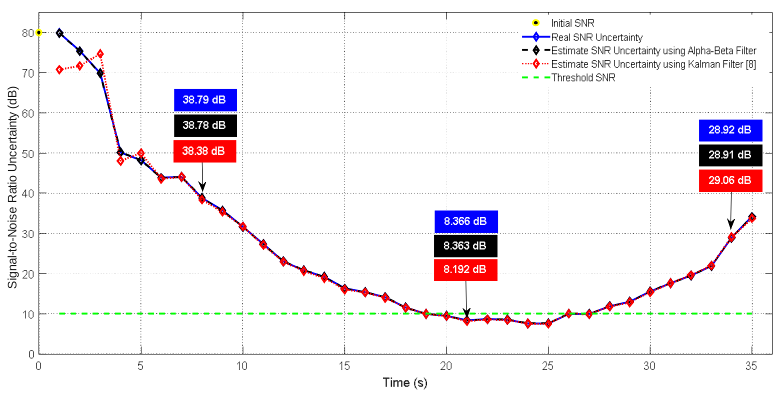


Fig. 7 SNR uncertainty (dB) versus time (s).

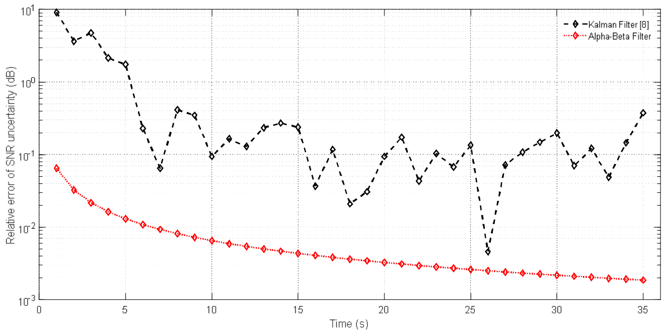
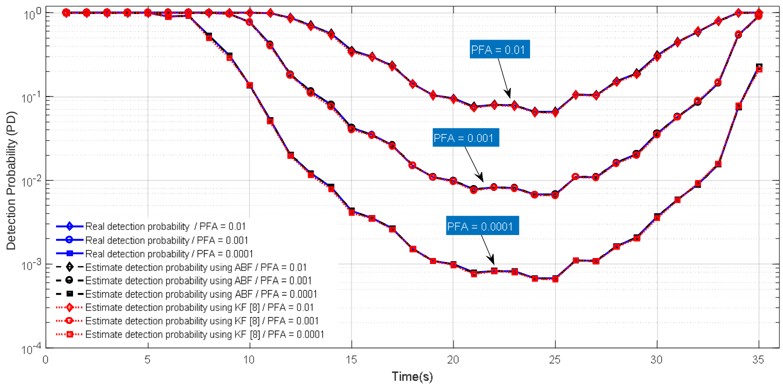
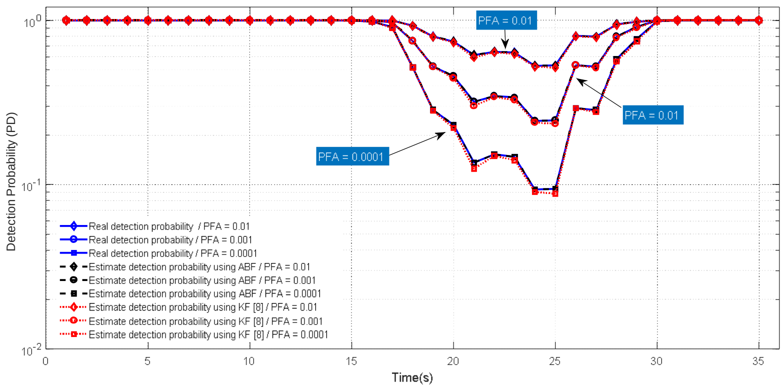


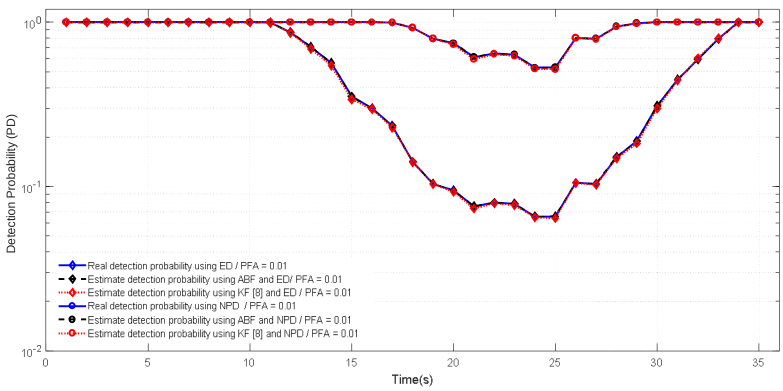
Fig. 8 Relative error of a SNR uncertainty (dB) versus time (s).



(a) Using ED.



(b) Using NPD.



(c) ED versus NPD with PFA = 0.01.

Fig. 9 Detection probability versus time (s).

In the third stage of the proposed algorithm, the effect of the SNR uncertainty on the primary signal sensing has been evaluated, using the detection probability (PD). It is clear from the Figs. 7 and 9 that the values of a PD increase as the SNR uncertainty increase. Therefore, we have noticed that at low values of the SNR uncertainty, it is very visible that the sensing performance of the primary signal deteriorates. It is also important to analyze the impact of the multipath and shadowing fading parameters on the sensing performance in CRNs. It is illustrated in Fig. 9 that the enhancement of PD can be optimized if using the NPD, in contrast to use the ED [8].

Additionally, the sensing performance of the primary signal, using the NPD provides an excellent average relative error of the PD. As an example, with the ABF, we can get an average relative error approximately equal to $9.2611 * 10^{-5}$, whereas the KF [8] provides an average relative error approximately equal to $8.9203 * 10^{-5}$ (see Fig. 10). Whereas, if we use an ED to sense the primary signals, the average relative error of the PD, with the ABF can be approximately equal to $2.5 * 10^{-3}$. In contrast to the KF [8], the average relative error of the PD can be approximately equal to $3.7 * 10^{-3}$ (see Fig. 11).

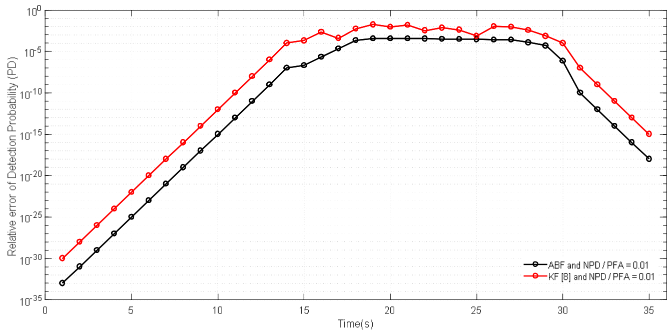


Fig. 10 Relative error of a PD using NPD versus time (s) with PFA = 0.01.

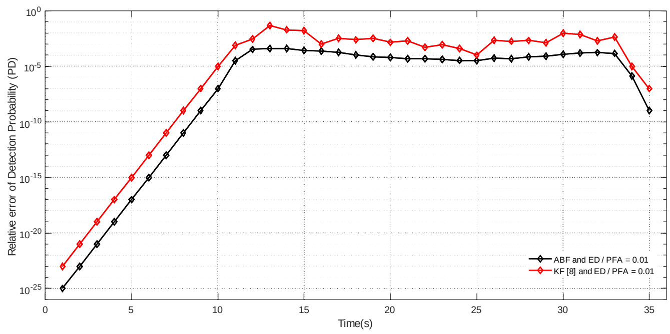


Fig. 11 Relative error of a PD using ED versus time (s) with PFA = 0.01.

4. CONCLUSION

In this article, we proposed and analyzed the performance of prediction method of primary signal strength in a crowded environment for cognitive radio networks, where the sensor (SU) is in motion. The designed algorithm is based on four methods to detect the primary signal transmitted, such as: KF-ED, KF-NPD, ABF-ED and ABF-NPD. The results of this analysis considerably quantify the effects of the crowded environment induced the shadowing and multipath fading, as well as the velocity of a sensor (SU) on the sensing performance. Moreover, the obtained results are shown that the sensing performance can be enhanced when the ABF-NPD method used. As example, the average relative error of prediction for the PD is approximately equal to 10^{-5}, as compared to the reference [15], the average relative error of prediction for the PD, has been equal to 10^{-4}. In the future we plan to detect the primary signal mask, where the KF used as an identifier of signal strength.

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