Journal of Engineering Sciences, Assiut University, Vol. 40, No. 3, pp. 867-875, May 2012

ADAPTIVE SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

Gamal Abdel Fadeel Mohammed
Electronics, Communications and Computer Engineering Department,
Faculty of Engineering, Helwan, Cairo, Egypt,
gam_hel@yahoo.com

(Received February 2, 2012 Accepted March 8, 2012)

It is becoming increasingly evident that cognitive radio (CR) users in CR networks acting in uncertain dynamical environments often employ exact or approximate Bayesian statistical calculations in order to continuously estimate the channel states. In this work we propose a prediction/filtering channel state estimation model capable of exactly implementing Bayesian state estimation and prediction from input point process measurements in real time. This setup is ideally suited to real CR networks. The results suggest that our model is useful for improving the performance of the sensing mechanism in practical CR environment.

KEYWORDS: *Cognitive radio networks; Adaptive sensing; Channel activity estimation; Hypotheses testing.*

1. INTRODUCTION

The traditional wisdom of spectrum management is top down, that is, frequency channels are assigned to users through licensed bands and only licensed users (primary users, PUs) can carry out communications over the allotted channels. A recent report from FCC shows that under this static allocation, merely 5% to 15% of the spectrum is utilized [1, 2]. Such a significant under-utilization has motivated a significant interest in studying cognitive radio (CR) networks. A CR is expected to capture temporal "spectrum holes" in the radio spectrum, and to enable secondary users (SUs) for spectrum sharing. A key functionality needed is the capability of sensing the spectrum and opportunistically using it without causing interference to the PUs. In this paper, we assume presence of N parallel, time-slotted-channels; each channel is assigned to a PU. The transmissions of PUs are modeled as a Markovian on-off process, with the "off" periods representing potential opportunities for the SUs. We assume also that SU can only sense one channel in each time slot and their sensing is noisy due to channel characteristics. The sensing error is, therefore, characterized by two basic parameters related to PU's activity: probability of false alarm $P_f =$ Pr (claim inactive | active) and probability of miss detection $P_m =$ Pr (claim active | inactive). In this respect, we propose an adaptive sensing scheme which adapts to PU's transmission activities. In this respect, use has been made of mathematical results from the theory of point process filtering in order to show how real-time state estimation and prediction of PU's activities can improve the performance of CR systems.

2. RELATED WORK

Optimal wireless medium access is derived within a Markovian framework between sensing and medium access. A significant number of sensing methods have already been proposed. These include, for example, energy detectors [3], cyclostationary detection [4], and eigenvalue-based sensing [5]. In this paper, we focus on energy detectors for its implementation simplicity. On the other hand, the usual approach to minimum mean square (MMSE) estimation has led to estimators that are intrinsically non-recursive and this is certainly a major drawback for their practical utilization. However, in [6], for example, it has been shown that the MMSE filtered estimates can be efficiently obtained as a linear transformation of the Posteriori Probabilities of the system states. In this paper we adopt an estimation scheme that is based on the Martingale Difference (MD) sequences which is something intermediate between statistical independence and un-correlation, so that independence implies the MD property which in turn implies un-correlation. This, in effect, has led to the so-called "MD Representation Theorem" [7].

Our approach is formulated within a point process framework based on discrete time approximations and input smoothing. As a result, using tools from the theory of point process filtering (e.g., [8]), in conjunction with the probabilistic Bayesian framework for dynamical state estimation (e.g., [9]). We are able to show that, a linear system suffices to yield an estimate for the posterior distribution for the state of a Markov process modeling the dynamics of PU activities in cognitive radio networks. The remaining of the paper is organized as follows: In Section 3, we present the CR channel activity modeling. In Section 4, we propose the prediction/filtering algorithm based on the point process. The hypotheses testing formulations is presented in section 4 as well. In Section 5, we evaluate the performance of the proposed detection scheme based on computer simulations. Finally, Section 6 concludes the paper

3. SYSTEM MODEL

Assume a cognitive radio system in which PU's activity-dynamics is characterized, at time t, by the state X_t belonging to an on-off Markovian process with idle/available, (0), and busy, (1), periods exponentially distributed with generator matrix Q:

$$Q = \begin{bmatrix} \mu & 1-\mu \\ \lambda & 1-\lambda \end{bmatrix} \quad (1)$$

Assume, also that, an energy detection scheme is being adopted for spectrum sensing. The reason for this choice is simply due to its implementation simplicity. In this respect, energy detection technique is mathematically formulated as a binary hypothesis testing problem on a set of N-samples that either represents just noise, or a signal in noise. This has led to the following formulations [10],

$$H_0: \quad Y_i := n_i, \qquad i = 1, 2, \dots, N \quad (2)$$

$$H_1: \quad Y_i := S_i + n_i, \qquad i = 1, 2, \dots, N$$

where Yi denotes complex baseband samples, n_i are noise samples, n_i: $CN(0, \sigma_0)$, and S_i denotes the signal samples drawn from a complex Gaussian, S_i : $CN(0, \sigma_1)$, This hypotheses testing problem is standard and the optimal Neyman-Pearson detector is, therefore, given by,

$$\Lambda(Y) = \sum_{i=1}^{N} Y_i^2 \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \quad (3)$$

where the threshold, γ, needs to be chosen such that the probability of false alarm (i.e., erroneously declaring a busy channel) is not greater than a specific value.

At this point, it is not difficult to see that, sensing is nothing but a sampling procedure of the given channel in order to discover it's (ON/OF) state at each sensing instant. Therefore, samples from ON/OFF periods leads to the values 1/0. In another words, sensing outcomes produces a random binary sequence for each channel. The problem we wish to consider is to approximate the random binary sequence at the output of a given channel-sensor as a discrete-time point-process. This point process is independent with arrival rate that is modulated by the time varying channel state X_t. Hence, while the channel state is not directly observable, it is only sensed through the point process observation sequence n(t), t = 1, 2, . . ., N. In the following sections, an estimate of the channel state from the past observations of the point process n(t) is presented and its performance is validated.

4. FILTERING OF THE MARKOV PROCESS FROM NOISY POINT PROCESS MEASUREMENTS

This section presents an estimation scheme for estimating the state of the unobservable (ON/OF) channel activities from point process observations n(t). Let $\{\beta\}^t$ represent all factors that affect the occurrence probability of the point process at time t. These factors include the past observations, $n^{t-1} = \{n(1), \ldots, n(t-1)\}$ and the past and present sequence of the hidden channel states, $x^t = \{x(1), \ldots, x(t-1), x(t)\}$. It can be shown (see Appendix) that the least square estimate, $x^\wedge(t+1)$ of the state x(t+1) given the observations $\mathcal{F}_t = \sigma\{n(1), \ldots, n(t-1), n(t)\}$ satisfies the following formula, [7, 12]

$$x^\wedge(t+1/t) = Q^T(t)X^\wedge(t/t-1) + \frac{\{S^T(t)\, X^\wedge(t/t-1) - Q^T(t)\,\Sigma(t)\,\rho(t)\}}{[\rho^T(t)X^\wedge(t/t-1)] - [\rho^T(t)X^\wedge(t/t-1)]^2} \cdot [n(t) - \rho^T(t)X^\wedge(t/t-1)] \quad (4)$$

and the filtered and smoothed estimate of X(t) given the past and present observations $\mathcal{F}_t = \sigma\{n(1), \ldots, n(t-1), n(t)\}$ is,

$$x^\wedge(t/t) = x^\wedge(t/t-1) + \frac{[diag(x^\wedge(t/t-1) - \Sigma(t)]\,\rho(t)}{[\rho^T(t)X^\wedge(t/t-1)] - [\rho^T(t)X^\wedge(t/t-1)]^2} \cdot [n(t) - \rho^T(t)X^\wedge(t/t-1)] \quad (5)$$

where, $S_{i,j}(t) = \Pr[\ X_j(t+1) = 1, n(t) = 1 \quad / X_i(t) = 1]$, $\Sigma(t) = X^\wedge(t/t-1)\, X^\wedge(t/t-1)^T$, the traffic intensity $\rho\,(t) = [\rho_1, \rho_2]$, and $x^\wedge(1/0)$ is the a priori of the signal.

Several observations are in place regarding equations (4, 5): (a) It provide optimal channel state estimator/filter given the train of point process observations. (b) The evolution of the state estimation, $x^\wedge(t+1/t)$ breaks up neatly into an observation independent term, which can be conceived as implementing a Bayesian dynamic prior, and an observation-dependent term, which contributes each time a point process occurs. Note that a similar structure was observed in [11]. In a more general setting, one can expect that the parameters of the Q-matrix to be learned on a slower time scale through interaction with the environment. We leave this as a topic for future work.

Now, for a cognitive user (SU), sensing a given channel, only two actions are available: to transmit or not to transmit. Therefore, we need a mapping from the estimation $x^\wedge(t/t) \rightarrow [0,1]$, i.e., from the expectations of the channel states as maintained by the SU to the transmission probability. Recall that we have assumed that the PU's channel transits from state 0 (idle/available) to state 1 (busy/unavailable) with probability $1-\mu$, and stays in state 1 with probability $1-\lambda$. Therefore, given that, our present knowledge of the channel state is $x^\wedge(t/t)$ (equ. (5)). Then, we propose that the SU updates his expectation on the channel according to the following Bayes rule,

$$\begin{bmatrix} \lambda\,(1 - x^\wedge(t/t)) + \\ \mu\, x^\wedge(t/t) \end{bmatrix} \underset{<_{busy}}{\overset{>^{idle}}{}} \begin{bmatrix} (1-\lambda) x^\wedge(t/t) + \\ (1-\mu)(1 - x^\wedge(t/t)) \end{bmatrix}, \tag{6}$$

where $\lambda\,(1 - x^\wedge(t/t))$ is the transition probability from busy to idle and $\mu\, x^\wedge(t/t)$ is from idle to idle, respectively. In the following section, we demonstrate how the Bayes rule (6) allows us to exploit the contribution of channel activity modeling in improving the miss/false detection probabilities in CR networks.

5. NUMERICAL SIMULATION

In this section, some numerical results are presented in order to illustrate the performance of the proposed sensing scheme using specific network parameters. The selections of these parameters are not crucial, and our simulation results are representative of the general behavior of the CR network. Here, we focus on the performance of a single CR user contending for access sharing with a given PU's channel. The activity of the channel is modeled by the ON/OFF states shown in Fig.(1), with sojourn times assumed to be exponentially distributed with parameters: $\lambda^{-1} = \mu^{-1} = 2$ ms, and with slot size T = 0.25 ms.

As shown in Fig. (1) below, when the cognitive user senses the channel, it collects the (1/0) point process at the outcome of the energy detector according to equ. (3), with the threshold, γ, used to regulate the trade-off between probability of false alarm and missing probability. For the noisy channel sensing scenario we look into, the sensing error that is characterized by the miss and false (point process) detections shown. The channel state is predicted using equ. (4). As can be seen, the prediction result approximates the overall behavior of the channel activity. In order to better approximate the busy periods of real channels. The prediction results are filtered, equation (5), and the results are shown in Fig. (2). Clearly, the filtered output provides a better protection for the PU's transmission by reducing the miss detection probabilities.

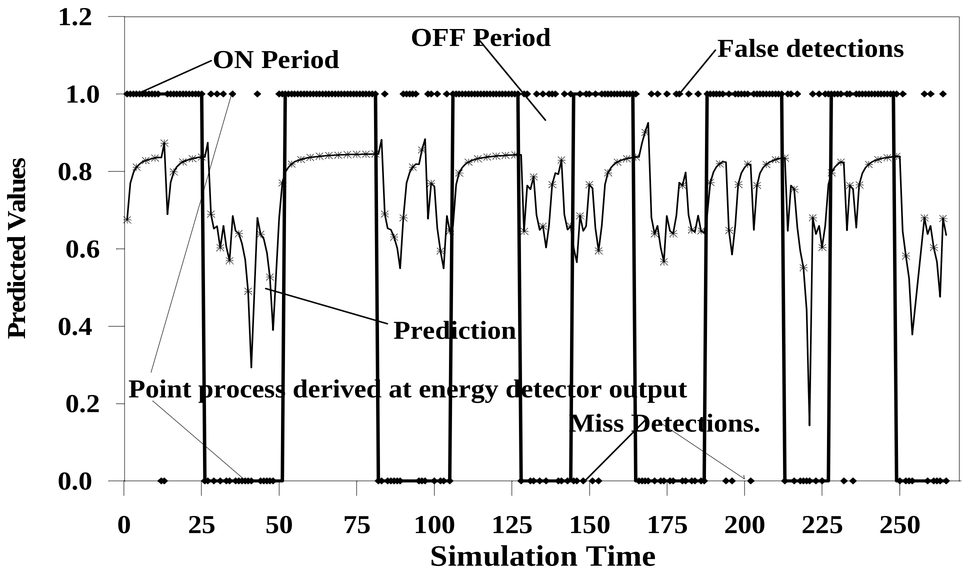

Fig.(1), PU' s (ON/OF) Activity Prediction

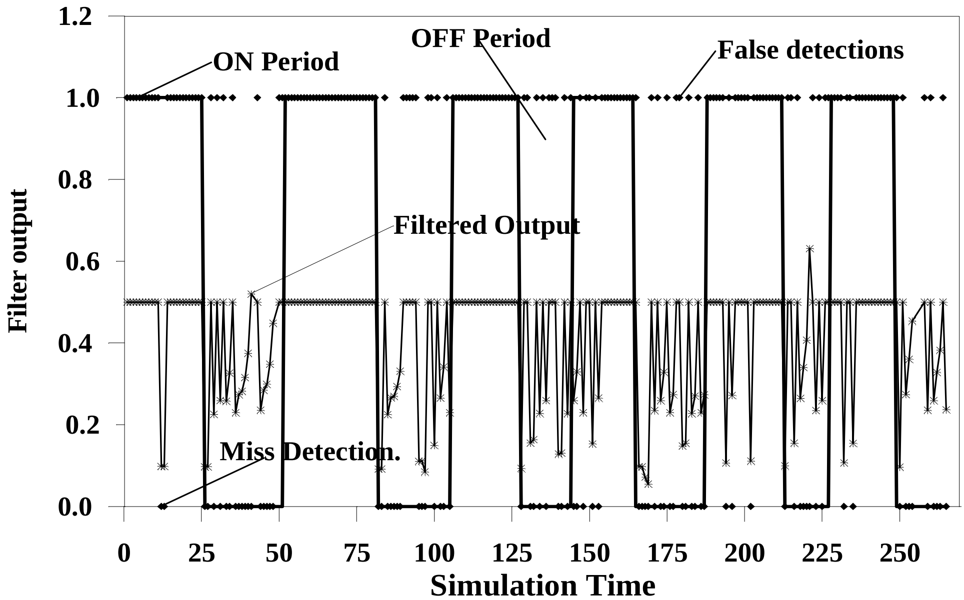

Fig.(2), PU' s (ON/OF) Activity Filtering

Comparing the predicted and the filtered results, we see that the overall behavior of the channel activity is reasonably approximated, and that the Markov modeling of the channel dynamics provides valuable evidences on channel activities. This, in turn, is expected to better reflect on the SU's predictions of the current state of the PU's channel.

Now, in order for the SU to transmit optimally, we have (section 4) parameterized the decision process as a Bayesian observer (SU) who collected expectations about the true state of the channel, $\hat{x}(t/t)$, and we combined it with the channel activity parameters (equ. (6)). The result is that, the SU is now able to decide on one of the two (to transmit or not to transmit) competing hypotheses. Fig.(3) shows the result of the hypotheses testing, i.e., likelihood ratio test (LRT). This result is processed in small, discrete time steps and the missing and false alarm probabilities are obtained as shown in Fig. (4). As can be seen, the simulation results show that the proposed sensing algorithm which is based on channel activity estimation/filtering with hypotheses testing performs is better than the energy detection without further (point process) processing. The implications of this result is that, the proposed sensing scheme, which adapts to channel activity dynamics, have led to a lower missing probability and (as it should according to Neyman Pearson) have maintained, almost, the same level of false alarm detections. In more specific terms, this simply means a better protection for the PU's transmissions (reduced interference from SU) while maintaining the same level of throughput for the SU.

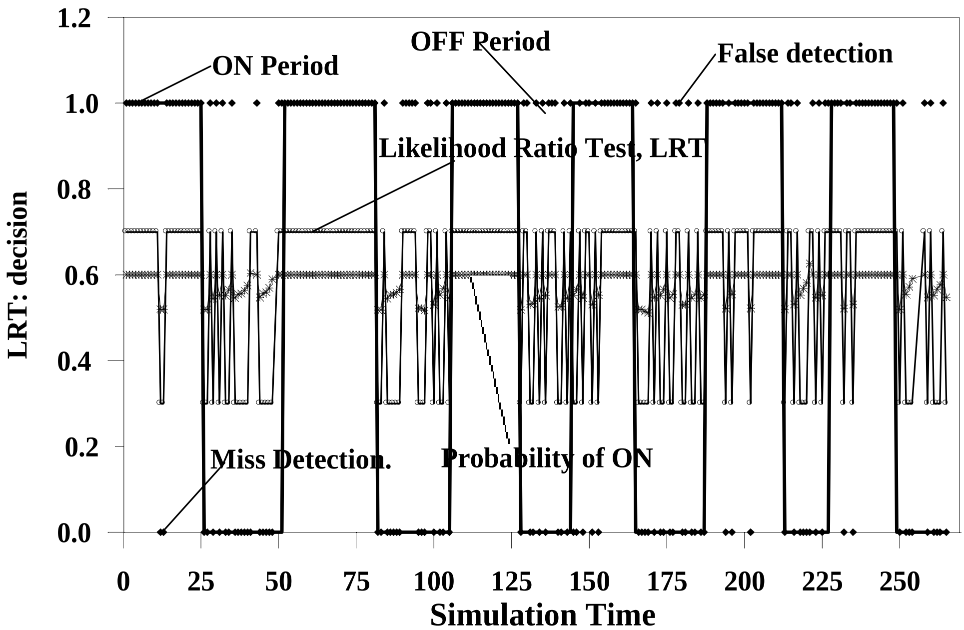

Fig.(3), PU' s (ON/OF) Hypotheses Testing (LRT).

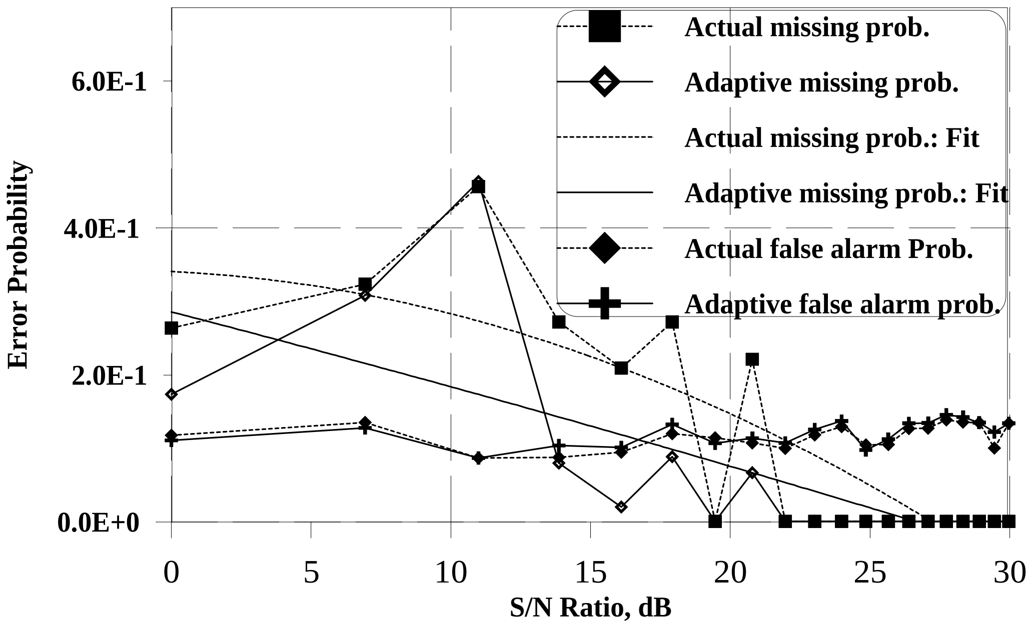

Fig.(4), Performance of adaptive sensing.

6. SUMMARY AND CONCLUSIONS

In this paper, we have presented a computationally tractable method for (channel) state-space and parameter estimation from point process observations. Results have indicated that this modeling approach have led to a better protection for the PU's transmissions while maintaining almost the same level of throughput for the SUs. The reason for such an improvement is that our model adapts efficiently to the PU's channel activity dynamics which, in turns, suggests that our model is useful for improving the performance of the sensing mechanism in CR networks.

APPENDEX

The innovation, representation concept and theory state that, the signal X(t) which influences the observations n(t) can be decomposed into predictable and unpredictable parts [12].

$$X(t+1) = E^{\beta_{t-1}}[X(t+1)] + [X(T+1) - E^{\beta_{t-1}}\{X(t+1)\}]$$

where β_{t-1} represents all factors that affect the occurrence probability, $\beta_{t-1} = \sigma\{n^{t-1}, x^t\}$ of X(t).

Therefore, define, $f(t, n^{t-1}, x^t)$= $E^{\beta_{t-1}}[X(t+1)]$, and u(t) = $[X(T+1) - E^{\beta_{t-1}}\{X(t+1)\}]$, we can write, X(t+1) = $f(t, n^{t-1}, x^t)$ + u(t), where u(t) is interpreted as some noise process.

Similarly, we can write, n(t) = $a(t, n^{t-1}, x^t)$ + w(t) for the point process observations. Now, define $\mu(t) = X^\wedge(t+1/t) - f^\wedge(t/t-1)$

The representation theorem states that every martingale difference sequence, $\mu(t)$ can be represented in terms of the innovation process, $n(t) - n^\wedge(t/t-1)$.

That is, $\mu(t) = g(t)v(t)$ where, $g(t)\ \frac{(\mu.v)_t}{(v.v)_t}$, and $(\mu.v)_t = E^{\mathcal{F}_{t-1}}\ \mu(t)v(t), and\ (v.v)_t = E^{\mathcal{F}_{t-1}}\ v(t)v(t)$.

In the Markovian signal settings which we look into in this paper, we find,

$a^\wedge(t/t-1) = \rho^T X^\wedge(t/t-1)$, and $u_i(t) = X_i(t+1) - \sum_{j=1}^{2} q_{ji} X_j(t)$,

$E^{\mathcal{F}_{t-1}}\ u(t)w(t) = E^{\mathcal{F}_{t-1}}\ [S(t)X(t) - Q^T X(t)X^T(t)\rho]$,

$(v\ v)_t = a^\wedge(t/t-1) - a^\wedge(t/t-1)^2$.

Hence, after some algebraic manipulations, the one step predictor and the filtering formulas can be found.

REFERENCES

[1] Anh Tuan Hoang and Ying-Chang Liang, "Adaptive Scheduling of Spectrum Sensing Periods in Cognitive Radio Networks", IEEE GLOBECOM 2007 proceedings.

[2] Xin Li, Qianchuan Zhao, Xiaohong Guan, " Optimal Cognitive Access of Markovian Channels under Tight Collision Constraints", IEEE journal on selected papers, in Commun. ,Vol. 29, NO. 4, APRIL 2011

[3] Yonghong Zeng, Ying-Chang Liang, Anh Tuan Hoang, and Rui Zhang, "A Review on Spectrum Sensing for Cognitive Radio: Challenges and Solutions", EURASIP Journal on Advances in Signal Processing, Volume 2010, page 15.

[4] A. Sahai and D. Cabric, “Spectrum sensing: fundamental limits and practical challenges,” in IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, November 2005.

[5] N. Han, S. H. Shon, J. O. Joo, and J. M. Kim, “Spectral correlation based signal detection method for spectrum sensing in IEEE 802.22 WRAN systems,” in Proceedings of the 8th International Conference on Advanced Communication Technology, Phoenix Park, South Korea, Febraury 2006.

[6] F. Penna, R. Garello, and M. A. Spirito, “Cooperative spectrum sensing based on the limiting eigenvalue ratio distribution in wishart matrices,” IEEE Communications Letters, vol. 13, no. 7, pp. 507–509, 2009.

[7] S. Galli, “Non Linear MMSE Estimation and SbS-MAP Receivers”, IEEE International Symp. on Inform. Theory, ISIT’00, Sorrento, Italy, 25-30 June, 2000.

[8] A. Segall, “Stochastic Processes in Estimation Theory”, IEEE Trans. on Inform. Theory, vol.22, no.3, pp.275- 286, May 1976.

[9] P. Br´emaud. "*Point Processes and Queues: Martingale Dynamics*", Springer, New York, 1981.

[10] R.P.N. Rao, "*Neural models of Bayesain belief propagation*", In K. Doya, S. Ishii, A. Pouget, and R. P. N. Rao, editors, Bayesian Brain, chapter 11. MIT Press, 2006.

[11] H. V. Poor, "*An Introduction to Signal Detection and Estimation*," 2nd ed. Springer-Verlag, 1994.
[12] A. Segall, "Recursive Estimation from Discrete Time Point Processes", IEEE Trans. On Info. Theory, vol. IT-22, no. 4, July 1976.

التقدير والتوقع المتابع لطيف التردد في شبكات اتصالات الراديو الادراكى

يقدم هذا البحث نظام لتقدير ومتابعة حالات قنوات الاتصالات اللاسلكية في نظم اتصالات الراديو الادراكى.
يعتمد هذا النظام على توظيف ما يعرف "بعملية النقاط" وذلك للوصول إلى تقدير وتوقع أفضل لحالات وتغير قنوات اتصالات الراديو والتي تتغير بصفه دائمه أثناء عمليات التواصل. أثبتت النتائج فاعلية هذا النظام في الحصول على تقدير وتوقع أفضل لتغير حالات قنوات الاتصالات، الأمر الذي أدى بدوره إلى تحسن ملحوظ في أداء هذا النوع من اتصالات الراديو الادراكيه.