Adaptive Sensing Schedule for Dynamical Spectrum Sharing in Time-varying Channel

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Adaptive Sensing Schedule for Dynamical Spectrum Sharing in Time-varying Channel

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***Abstract*—Dynamical spectrum sharing is considered as one of the key features in the next-generation communications. In this correspondence, we investigate the dynamical tradeoff between the sensing performance and the achievable throughput, in the presence of time-varying fading (TVF) channels. We first establish a unified dynamic state-space model (DSM) to characterize the involved dynamical behaviors, where the occupancy states of primary user (PU) and the fading channel gains are modeled as two Markov chains. On this basis, a promising dynamical sensing schedule framework is proposed, whereby the sensing duration is adaptively adjusted based on the estimated real-time TVF channel. We formulate the sensing-throughput tradeoff problem mathematically, and further show that there exists the optimal sensing duration maximizing the throughput for the secondary user (SU), which will change dynamically with channel gains. Relying on our designed recursive sensing paradigm that is able to blindly acquire varying channel gains as well as the PU states, the sensing duration can be then adjusted in line with the evolving channel gains. Numerical simulations are provided to validate our dynamical sensing schedule algorithm, which can significantly improve the SU's throughput by reconfiguring the sensing duration according to dynamical channel conditions.**

***Index Terms*—Sensing-throughput tradeoff, time-varying fading channel, dynamical sensing schedule, spectrum sensing, channel gain estimation.**

I. Introduction

The statistical data suggests that a large portion of the licensed spectrum are underutilized, leading to the spectrum scarcity problem. By permitting dynamical spectrum sharing, cognitive radio (CR) provides a new paradigm for opportunistic access of secondary users (SUs) to licensed bands, which are allocated originally to primary users (PUs) [1]. To share the primary band harmoniously without interfering the legal PUs, the SUs should firstly monitor a licensed band within a given amount of sensing time [2], and then opportunistically emit signals in transmission time-slots if none of the ongoing licensed operations are detected.

One of fundamental importance to CR networks is the tradeoff between the sensing accuracy and the SU's throughput, i.e. via an appropriate configuration of the sensing duration. That is, in the context of shared access, an optimal sensing duration should be determined, by maximizing the achievable shared throughput under the constraint that the PUs are sufficiently protected against harmful interference. Such an optimization problem was firstly considered by [3]. According to [3], the optimal sensing duration exists indeed, and a periodical sensing-transmission frame structure is proposed. Thereafter, the trade-off over Nakagami fading channel is considered in [4], which focused on the effects from fading parameters on the achievable throughput. In general, previous works assume the knowledge of wireless channels to be fully available at SUs, which will become impractical in some application scenarios, e.g. mobile or dynamic environments [5], [6]. Lately, an estimation-sensing-throughput tradeoff is proposed by [7] to solve the optimization problem with imperfect channel knowledge, which assumes SU can estimate the channel of PU-SU link. However, this approach ignores the dynamical nature of wireless environment and hence become less attractive. As far as we are aware, the dynamical sensing schedule in time-varying fading channels remains unexplored.

In this correspondence, we focus on the effects from time-varying fading (TVF) channel to sensing-throughput tradeoff, and thereby propose an adaptive sensing schedule to maximize the SU's throughput based on the real-time channel estimation. The main contributions are summarized into three aspects. Firstly, we formulate a dynamic state-space model (DSM) which fully characterizes the spectrum sharing system in the presence of TVF channel. In our stochastic model, the finite states Markov chains (FSMC) are utilized to model the dynamical evolutions of PU states and fading channel gains. Secondly, the sensing-throughput tradeoff is formulated as a dynamical optimization problem under the constraint condition of predefined sensing accuracy. We prove that there exists the optimum sensing duration for varying channels. Finally, a joint spectrum sensing algorithm is designed, which can estimate the TVF channel gains and detect the PU states. Relying on the real-time channel estimation, the adaptive configuration strategy for the optimum sensing duration is derived. Our dynamical sensing schedule scheme is optimal in the sense of the intergraded Bayesian sequential estimation and the consistence of the time-varying nature of fading channels.

The paper is organized as follows. In Section II, we formulate the DSM. The traditional sensing-throughput tradeoff problem is smartly introduced in Section III. In Section IV, the adaptive sensing schedule program with joint sensing algorithm is formulated. In Section V, numerical results are provided. Finally, conclusions are drawn in Section VI.

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The notations used are defined as follows. Symbols for vectors and matrices are in lowercase boldface and uppercase boldface respectively. $\mathbb{E}(\cdot)$ denotes the ensemble average. $|\cdot|$ denotes modulus operation. $Q(\cdot)$ denotes Q function which is the tail probability of standard normal distribution. SNR_{ps} denotes the signal-to-noise ratio (SNR) of PU-SU link, while SNR_{ss} denotes the SNR of SU-SU link.

II. System Model

Fig. 1 shows the frame structure designed for SU with periodic spectrum sensing (SS). Each frame T_f consists of one sensing slot $T_s(n)$ and one data transmission slot $T_t(n)$, i.e., $T_f = T_s(n) + T_t(n)$, $n = 0, 1, \cdots$. In the sensing slot, the detection result is obtained based on the sampling signals. $M(n)$ and τ denote the sampling size and sampling period respectively, $T_s(n) = M(n)\tau$. In this work, we design a dynamical sensing schedule scheme by considering TVF channel. Specifically, the frame period is fixed while the sensing duration may change adaptively relying on the transitional behavior of fading channel. Given the sampling frequency $f_s = 1/\tau$ is generally fixed for a receiving device, then the total sampling size $M(n)$ will be adjustable in the proposed sensing schedule.

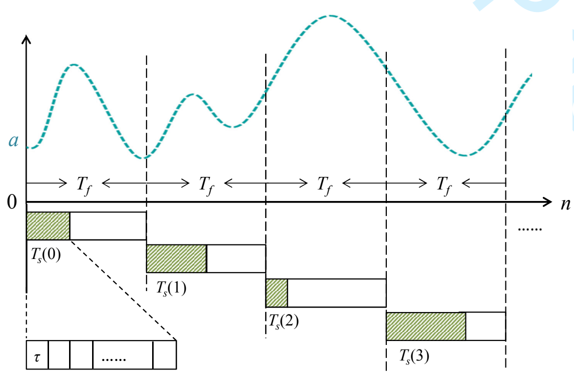

Fig. 1. Frame structure for SU with dynamical sensing duration

By incorporating the TVF channel, the discrete time DSM is formulated as:

$$[s(n), \mathbf{x}(n)] = \Phi([s(n-1), \mathbf{x}(n-1)]), \tag{1}$$

$$h(n) = \Psi(h(n-1)), \tag{2}$$

$$y(n) = \Omega(\mathbf{x}(n), h(n), \mathbf{w}(n)). \tag{3}$$

In the state equation (1), $s(n)$ denotes the PU state and comes into two forms: active $\mathcal{H}_1$ and dormant $\mathcal{H}_0$. $\mathbf{x}(n)$ represents the corresponding PU emitted signals, and we consider the complex PSK modulated signal under $\mathcal{H}_1$. The evolution behavior of PU state is characterized as a two-state Markov chain with the transition probability matrix (TPM) $\mathbf{P}_s$.

In the other state equation (2), $h(n) = a(n)e^{j\theta(n)}$ denotes the TVF channel state of PU-SU link at the nth slot, with fading amplitude $a(n)$ and phase $\theta(n)$. The amplitude a is assumed to be Rayleigh fading [8] and its statistical probability distribution function (PDF) with scale parameter σ_R^2 is:

$$f_A(a) = \begin{cases} \frac{a}{\sigma_R^2}\exp\left(-\frac{a^2}{2\sigma_R^2}\right), & a > 0, \\ 0, & a \leqslant 0, \end{cases} \tag{4}$$

and the fading channel phase θ is uniformly distributed as:

$$f_\Theta(\theta) = \frac{1}{2\pi}, \quad \theta \in [0, 2\pi). \tag{5}$$

Since our study focuses on the slow-fading case, we assume the fading channel changes at a rate much slower than the PU state, i.e. the coherence time of channel $T_c \approx 1/f_D$ is greater than the frame period T_f, where f_D denotes the maximum Doppler shift. Furthermore, the channel gain is assumed to be invariant within several successive frames, i.e., $T_c = JT_f$ and J is a positive integer. To this end, we define the *transition frame* (TF) as those frames when the channel gain will possibly vary and whose indexes are $n = lJ$ $(l = 0, 1, \cdots)$.

As far as TVF channel is considered, its amplitude varies randomly across a wide range. For two adjacent slots, however, the fading amplitude is highly correlated. I.e., the current fading state is related with the previous states. Thus, FSMC model is adopted owing to its effectiveness in modelling channel time-correlations [8]. In the FSMC model, the fading amplitude is partitioned to K non-overlapping regions, i.e., $[v_0, v_1), [v_1, v_2), \cdots, [v_{K-1}, v_K)$, and each region is represented by one feasible state A_k, $A_k \in [v_k, v_{k+1})$. The set of representative fading states is given by $\mathcal{A} = \{A_0, A_1, \cdots, A_{K-1}\}$. The amplitude $a(n) \in \mathcal{A}$ and evolves according to the first-order Markov process at the TFs but stays the same at the remaining frames (RFs). The TPM of the Markov process is $\mathbf{P}_a$.

Without losing the generality, the ED-based sensing is used and the observation equation (3) conditioned on two hypotheses is:

$$y(n) = \begin{cases} \sum_{m=1}^{M(n)} |w(n,m)|^2, & \mathcal{H}_0, \\ \sum_{m=1}^{M(n)} |a(n)x(n,m) + w(n,m)|^2, & \mathcal{H}_1. \end{cases} \tag{6}$$

Here, $w(n,m)$ denotes circularly symmetric complex Gaussian (CSCG) noise case. In the following analysis, we make the following assumptions for the above DSM.

(AS1) The PU emitted PSK modulated signals are an independent and identically distributed (iid) random process with mean zero and variance $\mathbb{E}\left[|\mathbf{x}|^2\right] = \sigma_x^2$. The noise is an iid random process with mean zero and variance $\mathbb{E}\left[|w|^2\right] = \sigma_w^2$. These two random processes are independent from each other.

(AS2) As the non-coherent detection is used, the amplitude-centric FSMC model is suitable, without considering the effects from channel phase to the observations, as shown in (6). Further, the evolution process of channel amplitude is independent of the PU states and noise process.

(AS3) The frames are expected to keep accordance with the changes of PU state. And the TFs are expected to keep accordance with the changes of channel amplitude.

III. Traditional Sensing-throughput Tradeoff

In this section, the regulatory constrains for sensing-throughput tradeoff under statical channel is presented, where the sampling size is constant, i.e., $M(n) \equiv M$.

A. Regulatory Constrains on Spectrum Sensing

The sensing performance is characterized with the probability of false alarm $p_f \triangleq p(y > \xi \mid \mathcal{H}_0) = \int_\xi^\infty p(y \mid \mathcal{H}_0)\,\mathrm{d}y$

and the detection probability $p_d \triangleq p(y > \xi \mid \mathcal{H}_1) = \int_{\xi}^{\infty} p(y \mid \mathcal{H}_1)\,\mathrm{d}y$, ξ is the detection threshold.

For a large M, $p(y \mid \mathcal{H}_0)$ can be approximated by a Gaussian distribution $\mathcal{N}\left(\mu_0, \sigma_0^2\right)$ based on the central-limit theorem, where $\mu_0 = M\sigma_w^2$ and $\sigma_0^2 = M\sigma_w^4$. Accordingly, $p(y \mid \mathcal{H}_1)$ can be approximated as another Gaussian distribution $\mathcal{N}\left(\mu_1, \sigma_1^2\right)$, $\mu_1 = M\sigma_w^2(\gamma + 1)$, $\sigma_1^2 = M\sigma_w^4(2\gamma + 1)$. Here, $\gamma = a^2\sigma_x^2/\sigma_w^2$ is the received SNR of the PU-SU link under $\mathcal{H}_1$.

The decision threshold ξ is chosen to obtain a certain detection probability $\bar{p}_d$ owing to the regulatory constraints from some telecommunication standards. For instance, $\bar{p}_d$ is chosen above 0.9 in IEEE 802.22 WRAN [9]. For the complex PSK modulated case with CSCG noise, p_d is calculated via:

$$p_d(\xi, M, \gamma) = Q\left(\frac{\xi - \mu_1}{\sigma_1}\right) = Q\left(\frac{\xi - M\sigma_w^2(\gamma + 1)}{\sigma_w^2\sqrt{M(2\gamma + 1)}}\right). \tag{7}$$

Then, the detection threshold ξ considering a target detection probability $\bar{p}_d$ can be determined by:

$$\xi = \sigma_w^2\left[\sqrt{M(2\gamma + 1)}Q^{-1}(\bar{p}_d) + M(\gamma + 1)\right]. \tag{8}$$

Finally, we derive the probability of false alarm as:

$$p_f(M, \gamma) = Q\left(\frac{\xi - \mu_0}{\sigma_0}\right) = Q\left(\sqrt{2\gamma + 1}Q^{-1}(\bar{p}_d) + \sqrt{M}\gamma\right). \tag{9}$$

B. Sensing-throughput Tradeoff under Statical Channel

As shown in Fig.1, the SU may emit in transmission slot depending on sensing results. The achievable throughput of SU is formulated when the PU is absence and no false alarm is generated. The probability of this scenario is $\left(1 - p_f\right)p(\mathcal{H}_0)$. Therefore, the throughput is calculated as $U(M, \gamma) = N\frac{T_f - M\tau}{T_f}C_0\left(1 - p_f(M, \gamma)\right)p(\mathcal{H}_0)$ [3]. Here, N denotes the total frames within specified time, $C_0 = \log_2(1 + SNR_{ss})$ and SNR_{ss} represents the SNR for the SU-SU link.

Since $Q(\cdot)$ is a monotonically decreasing function, we can have from (9) that the higher sampling size (i.e., longer sensing duration) can reduce the p_f for a given $\bar{p}_d$. However, the available data transmission duration becomes shorter that lead to the lower throughput. With an overall consideration of sensing capability and achievable throughput, the fundamental tradeoff can be stated as an optimization problem mathematically, i.e.

$$\max_{M} U(M, \gamma), \tag{10}$$

$$\text{s.t.} \quad p_d(\xi, M, \gamma) \geq \bar{p}_d. \tag{11}$$

And when choosing $p_d = \bar{p}_d$, the achievable throughput is:

$$\begin{aligned} U(M, \gamma) =& NC_0 p(\mathcal{H}_0)\frac{T_f - M\tau}{T_f}, \\ & \times\left[1 - Q\left(\sqrt{2\gamma + 1}Q^{-1}(\bar{p}_d) + \sqrt{M}\gamma\right)\right]. \end{aligned} \tag{12}$$

Existing methods give the optimization solution by obtaining the M corresponds to the maximum point of $U(M, \bar{\gamma})$ where $\bar{\gamma}$ is the expectation SNR_{ps}. However, in practical CR networks with wireless propagations, γ is commonly dynamical (e.g. due to TVF channel), and therefore, existing methods without considering the time-varying property of wireless link can only achieve an expected fair performance but is no longer optimal. To address this problem, we further design an adaptive sensing schedule.

IV. Adaptive Sensing Schedule

In this section, we first formulate the sensing-throughput tradeoff under TVF channel mathematically, then analyze the relation between the optimal sampling size and the PU-SU link SNR_{ps}. And finally, the adaptive sensing schedule which can solve the dynamical optimization problem is proposed.

A. Problem Formulation

As mentioned above, the channel amplitude a evolves as a FSMC process, and hence, the γ is also time-varying and the achievable throughput in (12) can be rewritten as:

$$U(M, \gamma) = C_0 p(\mathcal{H}_0)\sum_{n=0}^{N-1} u(M(n), \gamma(n)), \tag{13}$$

where $u(M(n), \gamma(n))$ denotes the throughput in one frame and,

$$u(M(n), \gamma(n)) = \left[1 - \frac{M(n)\tau}{T_f}\right]\left[1 - p_f(M(n), \gamma(n))\right]. \tag{14}$$

And then, the optimization problem in (10) and (11) can be restated as:

$$\max_{M(n)} u(M(n), \gamma(n)), \quad n = 0, 1, \cdots, N - 1, \tag{15}$$

$$\text{s.t.} \quad p_d(M(n), \gamma(n)) \geq \bar{p}_d. \tag{16}$$

Theorem 1: The maximum point of $u(M(n), \gamma(n))$ for $M(n)$ is exsiting and unique on one certain $\gamma(n)$ when $p_f(M(n), \gamma(n)) \leqslant 0.5$ but sensitivity to different $\gamma(n)$.

This theorem will hold if the following two propositions can be proven.

Proposition 1: There is a unique maximum point of the $u(M(n), \gamma(n))$ within the interval $M\tau \in (0, T_f)$.

Proposition 2: The optimal sampling size yields the highest throughput varies with respect to different $\gamma(n)$.

Proof for *Proposition 1*: For a target $\bar{p}_d$, the partial derivative of $u(M(n), \gamma(n))$ with respect to $M(n)$ can be derived as:

$$\begin{aligned} D(M(n), \gamma(n)) =& \frac{\partial u(M(n), \gamma(n))}{\partial M(n)}, \\ =& -\frac{\tau}{T_f}\left[1 - p_f(M(n), \gamma(n))\right] - \left[1 - \frac{M(n)\tau}{T_f}\right]\frac{\partial p_f(M(n), \gamma(n))}{\partial M(n)}, \\ =& -\frac{\tau}{T_f}\left[1 - Q(\beta(n))\right] + \frac{\gamma(n)\left[T_f - M(n)\tau\right]}{2T_f\sqrt{2\pi M(n)}}\exp\left[-\frac{\beta(n)^2}{2}\right]. \end{aligned} \tag{17}$$

where, $\beta(n) = \sqrt{2\gamma(n) + 1}Q^{-1}(\bar{p}_d) + \sqrt{M(n)}\gamma(n)$ and $p_f(M(n), \gamma(n)) = Q(\beta(n))$. Then, as $Q(\cdot)$ is monotonic decreasing and $Q(0) = 0.5$, we have:

$$\lim_{M(n)\tau \to 0} D(M(n), \gamma(n)) = +\infty, \tag{18}$$

$$\lim_{M(n)\tau \to T_f} D(M(n), \gamma(n)) < -\frac{\tau}{T_f}\left[1 - Q\left(\beta(n) - \sqrt{M(n)}\gamma(n)\right)\right] < 0. \tag{19}$$

We conclude from (18) and (19) that $D(M(n), \gamma(n))$ increases when $M(n)$ is small but decreases when $M(n)$ approaches T_f/τ. Thus, there exists a maximum point of $u(M(n), \gamma(n))$ within definitional domain $M(n) \in (0, T_f/\tau)$.

$$\frac{\partial^2 u(M(n),\gamma(n))}{\partial M(n)\partial\gamma(n)} = \frac{1}{\sqrt{2\pi}T_f}\exp\left[-\frac{\beta(n)^2}{2}\right]\left\{\frac{T_f - M(n)\tau}{2\sqrt{M(n)}} - \left[\frac{Q^{-1}(\bar{p}_d)}{2\sqrt{2\gamma(n)+1}} + M(n)\right]\left[\tau + \frac{T_f - M(n)\tau}{2\sqrt{M(n)}}\beta(n)\gamma(n)\right]\right\}. \quad (22)$$

As for the probability of false alarm,

$$\frac{\partial p_f(M(n),\gamma(n))}{\partial M(n)} = -\frac{\gamma(n)}{2\sqrt{2\pi M(n)}}\exp\left[-\frac{\beta(n)^2}{2}\right] < 0, \quad (20)$$

$$\begin{aligned}&\frac{\partial^2 p_f(M(n),\gamma(n))}{\partial M(n)^2},\\ &= \frac{\gamma(n)}{4\sqrt{2\pi}M(n)}\left[\frac{1}{\sqrt{M(n)}} + \gamma(n)\beta(n)\right]\exp\left[-\frac{\beta(n)^2}{2}\right].\end{aligned} \quad (21)$$

We can conclude from (20) that $p_f(M(n),\gamma(n))$ is decreasing with $M(n)$. Furthermore, when $\beta(n) \geqslant 0$, i.e., $p_f(M(n),\gamma(n)) \leqslant 0.5$, from (21) we have $\partial^2 p_f(M(n),\gamma(n))/\partial M(n)^2 > 0$ which means that $\partial p_f(M(n),\gamma(n))/\partial M(n)$ is monotonically increasing in $M(n)$, i.e., $p_f(M(n),\gamma(n))$ is convex. Therefore, from (17), it follows that $D(M(n),\gamma(n))$ is decreasing in $M(n)$, which further implies $u(M(n),\gamma(n))$ is concave in $M(n)$ when $p_f(M(n),\gamma(n)) \leqslant 0.5$. This indicate the maximum point of $u(M(n),\gamma(n))$ will be unique in this range.

Proof for *Proposition 2*: The mixed partial derivative of $u(M(n),\gamma(n))$ is shown by (22), which is impossible to become zero. Hence, we conclude that the optimal $M(n)$ satisfying $D(M(n),\gamma(n)) = 0$ will be associated with the varying SNR $\gamma(n)$ (or the dynamical channel gain).

Note that, since the channel gain $a(n)$ evolves as a FSMC process and $a(n) \in \mathcal{A}$, we can have that the $\gamma(n) = a(n)^2\sigma_x^2/\sigma_w^2$ evolves also as an FSMC process with the same TPM $\mathbf{P}_a$, and $\gamma(n) \in \mathcal{R} = \{R_0, R_1, \cdots, R_{K-1}\}$ where $R_k = A_k^2\sigma_x^2/\sigma_w^2$.

To this end, the reconfiguration relation between the optimal sampling size $M_k^\dagger$ and R_k can be presented as $\Delta = \left[\left\{R_0, M_0^\dagger\right\}, \left\{R_1, M_1^\dagger\right\}, \cdots, \left\{R_{K-1}, M_{K-1}^\dagger\right\}\right]$ which should meet the condition that $D(M_k^\dagger, R_k) = 0$. The key conception of our proposed adaptive sensing schedule is that the sampling size $M(n)$ (or the sensing duration) of each frame will be adapted with regards to the current $\gamma(n)$, which is determined via the reconfiguration relation above, i.e. $M(n) \in \mathcal{M} = [M_0^\dagger, M_1^\dagger, \cdots, M_{K-1}^\dagger]$.

B. Adaptive-Joint Sensing Algorithm

In order to accomplish the dynamical reconfiguration of the sampling size (or sensing duration) premised on the above reconfiguration relation, it needs now to implement the channel gain estimation (related with SNR_{ps}) and the PU state detection jointly.

1) Sampling size determination: Given the fact that the PU state and channel gain are unknown to SU at the current time n, the sampling size of current frame, i.e. $M(n)$, should be determined before jointly estimating channel gain and PU state relying on the observation $y(n)$. In our scheme, $M(n)$ is determined based on the predictive SNR_{ps}, i.e., $\gamma(n|n-1)$, with the reconfiguration set Δ. The $\gamma(n|n-1)$ is calculated via:

$$\gamma(n|n-1) = \begin{cases}\arg\max\limits_{\gamma(n)\in\mathcal{R}} p\left(\gamma(n)|\widehat{\gamma}(n-1)\right), & \text{TFs},\\ \widehat{\gamma}(n-1), & \text{RFs}.\end{cases} \quad (23)$$

where the prior probability $p\left(\gamma(n)|\widehat{\gamma}(n-1)\right)$ is obtained based on the TPM $\mathbf{P}_a$ and the estimated SNR_{ps} of the previous slot $\widehat{\gamma}(n-1)$, Then, if $\gamma(n|n-1) = R_k$, the sampling size $M(n)$ is reconfigured to $M_k^\dagger$, where $k \in \{0, 1, \cdots, K-1\}$. After reconfiguring the sampling size, we can obtain the observation according to the observation equation (6).

2) Channel gain estimation: Then, a joint estimation paradigm is suggested to estimate the channel gain and PU emitted signal jointly. From a Bayesian perspective, the joint estimation algorithm will be implemented via the maximum *a posteriori* probability (MAP) criterion [5], [6].

$$\begin{aligned}&[\widehat{a}(n), \widehat{\mathbf{x}}(n)]^{\text{MAP}}\\ &= \arg\max_{a(n)\in\mathcal{A}} p\left[a(n), \mathbf{x}(n) \mid \widehat{a}(n-1), \widehat{\mathbf{x}}(n-1), y(n)\right].\end{aligned} \quad (24)$$

where the posterior probability is decomposed into the multiplication of the likelihood function $p\left[y(n) \mid a(n), \mathbf{x}(n)\right]$ with the prior probabilities $p\left[a(n) \mid \widehat{a}(n-1)\right] p\left[\mathbf{x}(n) \mid \widehat{\mathbf{x}}(n-1)\right]$ which can be obtained by *a priori* TPMs $\mathbf{P}_s$ and $\mathbf{P}_a$ respectively.

3) PU state Detection: After the channel gain is updated, we can have the estimated SNR_{ps} as $\widehat{\gamma}(n) = \widehat{a}(n)^2\sigma_x^2/\sigma_w^2$. And then, the threshold $\xi(n)$ at the current frame for the target detection probability $\bar{p}_d$ can be calculated based on (8) with estimated SNR_{ps}. Thus, the detection result $\widehat{s}(n)$ is derived via the Neyman-Pearson (N-P) rule, i.e. $y(n) \underset{\mathcal{H}_1}{\overset{\mathcal{H}_0}{\lesseqgtr}} \xi(n)$.

C. Implementation

Based on the elaborations above, our new adaptive schedule and joint sensing algorithm can be realized recursively, and a corresponding schematic implementation is illustrated by Fig.2. The sampling size of current slot is adjusted firstly according to the predictive SNR_{ps} and the proposed reconfiguration relation. Then, the channel gain is estimated jointly with the PU emitted signal based on the MAP criterion. Once the update of channel gain is accomplished, then the threshold becomes available for making the final decision on the PU state of current frame.

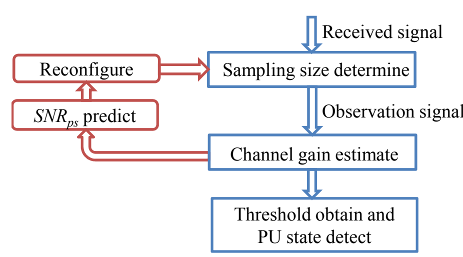

Fig. 2. Schematic implementation of the proposed adaptive sensing algorithm

V. Numerical Results and Discussions

In this section, computer simulations and discussions are presented to evaluate the sensing-throughput tradeoff performance of proposed schedule. We choose $p(\mathcal{H}_1) = 0.5$,

$\bar{p}_d = 0.9$, $T_f = 500$ms, $N = 5000$, the SNR for SU-SU link $SNR_{ss} = 20$dB, and hence, $C_0 = \log_2(1 + SNR_{ss}) = 6.6582$. The PU emitted signal is assumed to be QPSK modulated with bandwidth of 6MHz [3] and the additive noise is a zero-mean CSCG process. The maximize Doppler shift $f_D = 0.05$, and the partitioning number of channel state $K = 8$.

We first show the joint impact of the sampling size M and the channel gain a on the SU's achievable normalized throughput, which is defined as $U^{\dagger} = U/(NC_0)$. Fig.3 suggests $U^{\dagger}(M, a)$ dramatically changes with both sensing duration M and channel gain a. Fig.4 illustrated the utility surface $D(M, a)$ with the zero-flat, where the intersection line corresponds to the optimal sampling size for a given channel. We observed that the optimal sampling size maximizing the achievable throughput is uniquely determined by channel gain which hence varies with different channel states. So, numerical results further validate the previous analysis in *Theorem 1*.

In Fig. 5, we compared the maximum throughput of various configurations of sensing durations in time-varying channels. It is seen that the throughput performance of our adaptive sensing schedule, with the jointly estimated channels, may approach the ideal performance (i.e. with the known channels), which further validate our designed joint channel estimation algorithm. From Fig. 5, its performance significantly outperforms static sensing schedule schemes. For example, when $SNR_{ps} = 0$dB, the throughput of our new adaptive allocation is 20% higher than a static schedule with the estimated average channel gain, while is more than 300% higher than a static schedule without channel estimations.

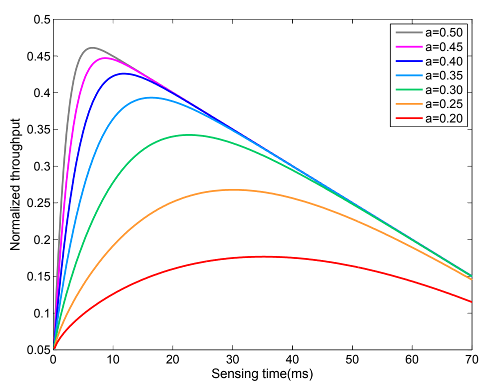

Fig. 3. SU's throughput versus the sampling size and fading channel gain

Note that, the reconfiguration can be implemented off-line (provided channel statistics, e.g. distribution variance). Thus, the predictive function in (23) can be also implemented via another FSMC. Once the pervious fading state is acquired, the current sensing samples can be then determined directly.

VI. Conclusions

In this correspondence, we consider the sensing-throughput tradeoff problem in dynamical environments and design an adaptive sensing schedule scheme. Particularly, we show the optimal sensing duration (maximizing the shared capacity) is closely related with dynamical channel gains. A joint sensing algorithm with adaptive sensing duration is then proposed. Simulation results are provided to validate the designed

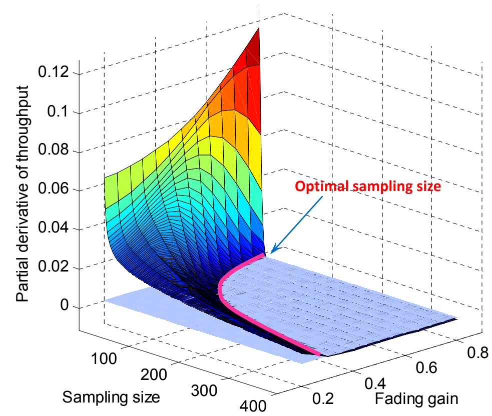

Fig. 4. Partial derivative of throughput versus the sampling size and fading channel gain

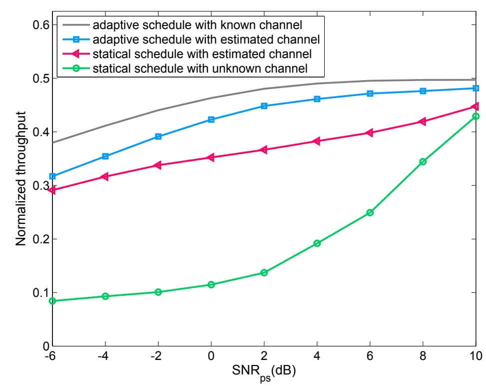

Fig. 5. Throughput performance comparison

scheme, with which the significant improvement in shared throughput can be attained.

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