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# ENERGETIC SPECTRUM SENSING FOR COGNITIVE RADIO ENABLED REMOTE STATE ESTIMATION OVER WIRELESS CHANNELS

Author : [1] C.Jenita Blesslin (PG Scholar), [2] Mr.S.Esakki Rajavel (Assistant Professor, Dept of ECE)
Mail id : [1] jeniblessyy@gmail.com, [2] rajavel019@gmail.com
M.E. Communicaiton Systems(2014-16), Francis Xavier Engineering College
Affiliated to Anna University Chennai

**ABSTRACT-**The performance of remote estimation over wireless channels is strongly affected by sensor data losses due to interference. Although the impact of interference can be alleviated by applying cognitive radio technique which features in spectrum sensing and transmitting data only on clear channels, the introduction of spectrum sensing incurs extra energy expenditure. Investigating the problem of energy efficient spectrum sensing for remotely estimating the state of a general linear dynamic system, and formulate an optimization problem which minimizes the total sensor energy consumption while guaranteeing a desired level of estimation performance. Simulation results achieve the desired estimation performance.

## I. INTRODUCTION

Estimating the states of dynamic processes is a fundamental task in many real-time applications such as environment monitoring, health-care, smart grid, industrial automation and wireless network operations [2]–[4]. Among existing estimation algorithms, we consider Kalman filtering which has been widely applied for estimating the state of wireless channels [6], local power of a mobile station in cellular networks, and number of active terminals in wireless local area networks etc. In many cases, sensor measurements are transmitted through wireless media to a remote estimator which then performs state estimation and makes certain decisions based on the estimation results.

In this paper, we study the problem of energy-efficient spectrum sensing strategy for state estimation, aiming at systematically addressing the above four fundamental issues. Specifically, focusing on a general linear dynamic process, we consider the problem of minimizing the energy consumption of the sensor while guaranteeing a desired level of estimation performance. The main contributions of this paper can be summarized as follows. 1) We provide a cyber-physical model of the whole system for state estimation and formulate the above optimization problem as a mixed integer nonlinear program (MINLP), subjecting to an estimation performance constraint. 2) We first exploit the single-channel case and derive a condition under which the estimation error covariance is stable in mean sense. Since the mean estimation error covariance is usually a random value and may vary slightly but not converge along time, the explicit expression for the mean estimation error covariance is difficult to obtain. We thus resort to a close approximation of the constraint which results in an approximated optimization problem whose solution suffices the original problem. We

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also provide analytical results of the optimization solution.

## II. RELATED WORK

The stability of Kalman filter under random packet losses has gained intensive studies recently. In the case that the packet losses are independently and identically distributed, the estimation error (in mean square sense) is stable only when the packet loss rate is below a certain bound [5]. Recently, there has been a large volume of literature investigating the problem of state estimation stability in various wireless communication situations, e.g., Markovian and semi-Markov packet losses and more general packet loss processes. These results explicitly show that the estimation stability heavily depends on the packet loss process. However, most studies consider only one wireless channel for sensor data transmission. Basically, there are two major challenges in the application of spectrum sensing for remote state estimation over multiple wireless channels. First, the spectrum sensing results may be inaccurate, which in turn affects the subsequent transmission successfulness and consequently the estimation performance. With inaccurate spectrum sensing, the question of whether and to what extent the state estimation performance can be improved is addressed. Energy efficiency is an important design issue for today's wireless systems. System energy efficiency is the second challenging issue which further introduces the sensor scheduling, channel selection, sensing order and sensing time optimization problems. It has been proved that the optimal data transmission schedule can be approximated by periodic (not necessarily strictly periodic) scheduling with arbitrarily close performance. From the energy perspective, for a class of state estimation problems over a finite long time horizon, it also has been shown that the optimal sensor schedule is to distribute the data transmission time along the time horizon as uniform as possible. Christo Ananth et al. [3] discussed about Improved Particle Swarm Optimization. The fuzzy filter based on particle swarm optimization is used to remove the high density image impulse noise, which occur during the transmission, data acquisition and processing. The proposed system has a fuzzy filter which has the parallel fuzzy inference mechanism, fuzzy mean process, and a fuzzy composition process. In particular, by using no-reference Q metric, the particle swarm optimization learning is sufficient to optimize the parameter necessitated by the particle swarm optimization based fuzzy filter, therefore the proposed fuzzy filter can cope with particle situation where the assumption of existence of "ground-truth" reference does not hold. The merging of the particle swarm optimization with the fuzzy filter helps to build an auto tuning mechanism for the fuzzy filter without any prior knowledge regarding the noise and the true image. Thus the reference measures are not need for removing the noise and in restoring the image. The final output image (Restored image) confirm that the fuzzy filter based on particle swarm optimization attain the excellent quality of restored images in term of peak signal-to-noise ratio, mean absolute error and mean square error even when the noise rate is above 0.5 and without having any reference measures. The problems of channel selection and channel sensing order are mostly studied within the communication community.

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## III.CYBER PYSICAL SPACE

Cyber-physical systems (CPS) are physical and engineered systems whose operations are monitored, coordinated, controlled and integrated by a computing and communication core. Many grand challenges await in the economically vital domains of transportation, health-care, manufacturing, agriculture, energy, defense, aerospace and buildings. The design, construction and verification of cyber-physical systems pose a multitude of technical challenges that must be addressed by a cross-disciplinary community of researchers and educators. Consider that the process is periodically sampled by a wireless sensor and the measurement data will be transmitted to a remote estimator. At the beginning of each sampling period (also called step), the sensor first takes a measurement of the target dynamic system state and transmits this measurement packet to the remote estimator over a wireless channel.

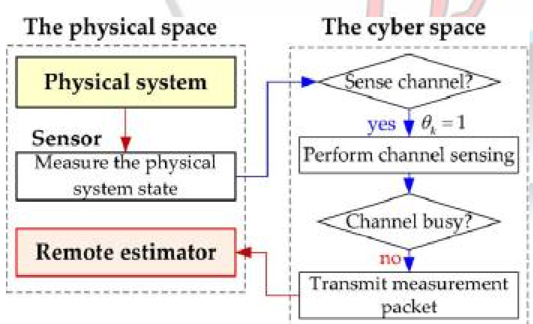


**Fig. 1. A cyber-physical view of the system architecture.**

The sensor data transmission is augmented by the spectrum sensing technique. A transmission will be unsuccessful, i.e., a packet drop will happen, if the sensor transmits the packet when the channel is busy. The whole system can be described from a cyber-physical point of view. Fig. 1 illustrates the interactions between the cyber and physical spaces for state estimation over one wireless channel. The main notations used throughout this paper are listed in Table I. E[·] and P[·] denote the expectation and probability of a random variable, respectively. $(\cdot)T$ denotes the transpose of either a vector or a matrix while $trace(\cdot)$ denotes the trace of a matrix.

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**TABLE I**
**BASIC NOTATIONS**

| NOTATION | DEFINITION |
|---|---|
| $X_k$ | State of the target dynamic system at the beginning of step k |
| $Y_k$ | Sensor measurement about the dynamic system state in step k |
| $\gamma_k$ | Binary variable indicating whether $Y_k$ is successfully transmitted and received by the estimator in step k |
| $T_s$ | Sensor's sampling period |
| $t_x$ | Transmission time of each measurement packet (the packet lengths are assumed the |

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| | |
|---|---|
| | same |
| $CH_i$ | The i-th channel |
| $\tau_i$ | Channel sensing time over $CH_i$ |

### A. PHYSICAL SPACE

The target dynamic system is modeled as follows (the discrete time steps are determined by the sensor's sampling period $Ts$):

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{w}_k$$

where $\mathbf{x} \in R^{q1}$ is the system state and $q_1$ is its dimension, $\mathbf{w}$ is the system noise with $E[\mathbf{w}_k \mathbf{w}^T_k] = \mathbf{Q} \geq 0$, $\mathbf{A}$ is a constant square matrix modeling the state dynamics in two successive time steps.

The sensor measurement of the system state in $k$th step is modeled as

$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k + \mathbf{v}$$

where $\mathbf{v}$ is the measurement noise with $E[\mathbf{v}_k \mathbf{v}^T_k] = \mathbf{R} \geq 0$ and $E[\mathbf{w}_i \mathbf{v}^T_j] = 0$. $\mathbf{y} \in R^{q2}$ (where $q_2$ is its dimension) and $\mathbf{C} \in R^{q2 \times q1}$ . Both $\mathbf{w}$ and $\mathbf{v}$ are assumed Gaussian with zero means. Assume that $\mathbf{C}$ has full column rank for simplicity.

The estimator applies the following modified Kalman Filter to estimate the system state $\mathbf{x}$ recursively. Define $\mathbf{x}\hat{}_{k|k-1}$ and $\mathbf{x}\hat{}_{k|k}$ as the prediction and estimate of the system state at step $k$, respectively. Define $\mathbf{P}_{k|k-1}$ and $\mathbf{P}_{k|k} = E[(\mathbf{x}_k - \mathbf{x}\hat{}_{k|k})(\mathbf{x}_k - \mathbf{x}\hat{}_{k|k})^T]$ as the covariance of the prediction and estimation errors, respectively. The prediction can be calculated based on the system model as : $\mathbf{E[(x_k - x\hat{}_{k|k-1})(x_k - x\hat{}_{k|k-1})^T}$ ] without receiving the measurement of the current system state from the sensor, the estimator has to use the prediction to update its estimate i.e., $\mathbf{x}\hat{}_{k|k} = \mathbf{x}\hat{}_{k|k-1}$ and $\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1}$

### B.CYBER SPACE

The main task of the cyber sub-system is to decide whether to sense the channel and to transmit the measurement packet in each step. Cyberspace is a domain characterized by the use of electronics and the electromagnetic spectrum to store, modify, and exchange data via networked systems and associated physical infrastructures.

Let $t_I$ and $t_B$ represent the idle and busy periods of the channel, respectively. They model the activities of all users other than the sensor on that channel over a long time. Let $E[t_I]$ and $E[t_B]$ be the average idle and busy periods respectively.

Define,

$\rho = \frac{E[t_B]}{E[t_I]}$ which is an important characteristic of the channel.

The probabilities that the channel is idle and busy are respectively,

$$P_I = \frac{1}{1+\rho}$$

$$P_B = \frac{\rho}{1+\rho}$$

Let $sc$ be the sensing outcome (with 0 indicates idle and 1 otherwise) and define following two probabilities.

$$\mathrm{p_d} = \mathrm{P}[\mathrm{s_c} = 0]_{\text{Channel idle}}$$

$$p_d = P[s_c = 0]_{\text{Channel busy}}$$

Where,

$S_c$ be the sensing outcome (with 0 indicates idle and 1 otherwise)

The transmission probability as,

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$$p_{tx} = p_I p_d + p_B p_f$$

The successful packet transmission rate can be given as follows:

$$\gamma = \frac{n}{1+\rho} p_d$$

$p_d$ and $p_f$ are the correct and false detection robabilities In this, after sensing the channel, the sensor will transmit packet only if sensing result indicates an idle channel.

## IV. OPTIMIZATION IN SINGLE-CHANNEL CASE

Process optimization is the discipline of adjusting a process so as to optimize some specified set of parameters without violating some constraint. The most common goals are minimizing cost, maximizing throughput, and/or efficiency. This is one of the major quantitative tools in industrial decision making. When optimizing a process, the goal is to maximize one or more of the process specifications, while keeping all others within their constraints. The stability of the estimation error in mean square sense are utilized. Then we present problem approximation which ensures the problem tractability.

To satisfy the estimation, {E[**P**k]} must be stable,

i.e.,E[**P**$k$] < ∞, ∀$k$ ≥ 1.

For any $k \geq 1$, if $\theta k = 1$, based on the estimation process as,

$$p_k = (1-\gamma_{k)} A P_{k-1} A^T + \ Q\ \gamma_k A \gamma_{k-1} A^T$$

The condition for the stability of {E[**P**k]} which is both necessary and sufficient. The stability with respect to model uncertainty of linear estimators of the coefficients of a linear combination of deterministic signals in noise is investigated. A class of estimators having nominal performances constrained to be close to that of the nominal linear, unbiased, minimum-variance (LUMV) estimator is specified. Two estimator stability indexes are defined, one based on a worst-case estimate mean-square error and the other on a type of signal-to-noise ratio.An optimal solution is a feasible solution where the objective function reaches its maximum value, the most profit or the least cost. A globally optimal solution is one where there are no other feasible solutions with better objective function values. Optimal schedule Θ$n$ and channel sensing time τ to

$$\varphi = \frac{1}{n}(\tau e_s + p_{tx} e_{tx})$$

The optimal sensing time τ drops quickly as the idle probability increases, which results in the decrease of the average energy consumption ϕ.

## V. SIMULATION RESULTS

In this section, we conduct simulations to demonstrate the effectiveness of the proposed method. We consider a linear system (1) with **A** =[1.05 0] , [1 0.9] , **C** = **I**, **Q** = **I** and **R** = 0.8**I**, where **I** is the 2-by-2 identity matrix. The sensor samples the system every $Ts$ = 1 second and the transmission time of each measurement packet is $tx$ = 50ms. The estimation performance requirement is set as ¯**P** = ¯**Y**(0.7,6).

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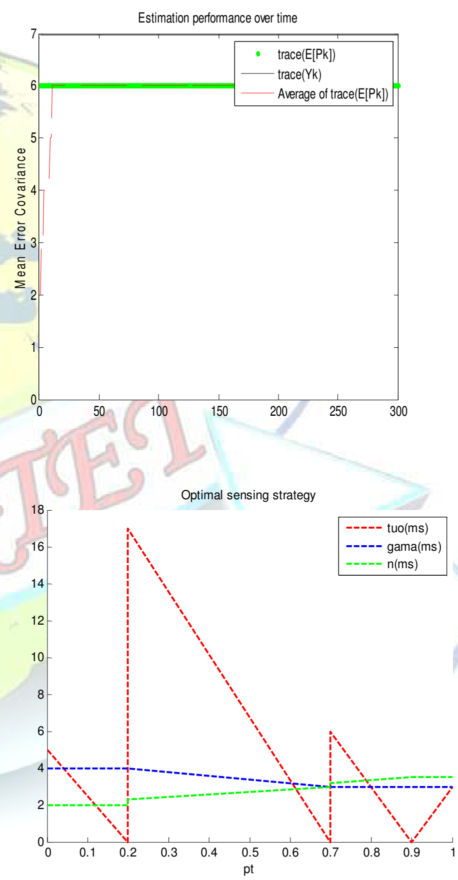
For the channel under consideration, we assume its bandwidth $W$ = 2MHz and noise power ʃ$n$ = 1mW. The signal-to-noise ratio of the signal received by the sensor during the channel's busy periods is −3dB. The average channel busy and idle rates 〈 = 5 and ® = 30, respectively. The sensing parameter ∑$d$ = 1.2, the maximum sensing time is ¯| = 250 units with the unit channel sensing time as 0.1 ms. The per-second energy cost of sensing and transmitting is $es$ = $etx$ = 100 unit. Fig. 2(a) shows an example trace of the estimation error covariance along time, where the sensor conducts sensing every step (i.e., $n$ = 1) and the sensing time on the channel is fixed at 1 ms. The curve of E[**P**$k$] is obtained by averaging the results of 2000 independent simulation runs. As discussed before and also shown in this figure, E[**P**$k$] does not converge. However, the figure indicates that the upper bound curve **Y**$k$ is a good approximation of the long-term average of E[**P**$k$]. The optimal solutions are depicted in Fig. 2(b), where we vary the channel idle probability $pI$ by gradually increasing ®. The results show that, under a certain $n$, the optimal sensing time drops quickly as the idle probability increases, which results in the decrease of the average energy consumption. In fact, as the channel quality becomes better, less sensor energy will be wasted for conducting sensing and transmitting during the channel's busy periods. Meanwhile, when $pI$ increases from 0.3 to 1, the optimal $n$ increases piecewise, which means that the sensor conducts spectrum sensing and packet transmission less frequently. Therefore, generally speaking, the energy consumption decreases as $pI$ increases.

**Fig. 2. Performance in the single-channel scenario. (a) Estimation performance over time. (b) Optimal sensing strategy.**




## VI. CONCLUSION

The energy-efficient spectrum sensing problem for remote state estimation over channels. By applying cognitive radio technique which features in spectrum sensing and transmitting data only on clear channels, the introduction of spectrum sensing incurs extra energy expenditure. In

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Cognitive radios technique support wireless users in crowded spectrum and avoid interferences. Efficiently utilized in advanced communication system techniques and signal processing techniques. Future directions include extending the idea to multiple channel and multiple sensor scenarios.

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