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Optimal Real-Time Estimation Strategies for a Class of Cyber-Physical Systems Using Networked Mobile Sensors and Actuators

Christophe Tricaud & YangQuan Chen
Center for Self-Organizing and Intelligent Systems (CSOIS)
Utah State University, Logan, UT84322-4160, USA
Emails: ctricaud@gmail.com; yqchen@ieee.org

1. Introduction

The combination of physical systems and networks has brought to light a new generation of engineered systems: Cyber-Physical Systems (CPS) (CPS, 2008). CPS is defined in (Chen, 2008) in the following way: ``*Computational thinking and integration of computation around the physical dynamic systems form Cyber-Physical Systems (CPS) where sensing, decision, actuation, computation, networking and physical processes are mixed*''. CPS is foreseen to become a highly researched area in the years to come with its own conferences (NSF, 2006; WCPS, 2008) and journals, e.g. (Gill *et al*, 2008).

``*Applications of CPS arguably have the potential to dwarf the 20-th century IT revolution*'' (Lee, 2007). CPS applications can be found in medical devices and systems, patient monitoring devices, automotive and air traffic control, advanced automotive systems, process control, environmental monitoring, avionics, instrumentation, oil refineries, water usage control, cooperative robotics, manufacturing control, buildings, etc.

The first step when considering a CPS is to determine the dynamics of its ``physical'' part, i.e. the environment in which the sensors and actuators are going to operate. First by defining a matching mathematical model, and then by retrieving the values of the parameters of this model. In this paper, the parameter estimation process constitutes a CPS in itself as we are using a mobile actuator-sensor network for that purpose.

The ``modeling-analysis-design (MAD)'' process in dynamic systems control is fundamental in control engineering practice. In both physical and mathematical modelling, the parameter estimation is essential in successful control designs.

A precise parameter estimation depends not only on ``relevant'' measurements and observations, but also on ``rich'' excitation of the system. These are all known concepts in system identification for finite dimensional systems (Ljung, 2008).

In control engineering practice, it is very common to estimate the parameters of a system given a mathematical model. Using observations or measurements, one can parameterize the model using different techniques. Sometimes, when the system to be modelled is spatially and temporally dynamic (i.e. the states depend on both time and space), common

lumped parameter input-output relationships cannot characterize the system dynamics and instead, we must use partial differential equations (PDEs) for modelling.

However, making observations or measurements of the states of a distributed parameter system is not an easy and straightforward task. One needs to consider the location of the sensors so that the gathered information best helps model parameter identification. This problem of sensor location is not new but most of the work achieved so far is limited to stationary sensors in the context of wireless sensor networks (Kubrusly & Malebranche, 1985 ; Uciński, 2005).

Mobile sensors that are now available both via mobile robots or unmanned air/surface/underwater vehicles, offer a much more interesting alternative to stationary sensors for distributed parameter systems characterization. Indeed, when looking for optimal location of a stationary sensor, one only seeks the optimal average over time and space. However, the optimal location to gather sensible data about a given distributed parameter system is not necessarily static but in most cases, dynamic. It is therefore logical to expect a better estimation of the PDE-based system if mobile sensors are used than only considering stationary sensors.

Areas of application of such mobile sensing techniques include air pollutants monitoring using cars equipped with sensors on the ground and aircrafts in the air. In addition, low cost platforms for mobile sensors with wireless communications are now available and becoming cheaper and cheaper. As said, a set of such autonomous vehicles equipped with sensors can potentially improve the efficiency of the measurements. As technology evolves, it is necessary and practically meaningful to consider using mobile sensors for optimal measurement of distributed parameter systems with an objective of unknown parameters estimation.

In this chapter, we consider this type of research problem first introduced in (Walter & Pronzato, 1997), where the optimal observations of a DPS based on diffusion equations were made by two-wheeled differentially driven mobile robots equipped with sensors.

In the field of mobile sensor trajectory planning in a distributed parameter system setting, few approaches have been developed. So far, the available solutions are not quite practically appealing. For example, Rafajówicz (Rafajówicz, 1986) investigated the problem using the determinant of the Fisher Information Matrix (FIM) associated with the parameters to be estimated. The determinant of the FIM is used as a metric evaluating the accuracy of the parameters estimation. However, the results are more of an optimal time-dependent measure than a trajectory. In (Uciński, 2000) and (Uciński, 2005), Uciński reformulated the problem of time-optimal path planning into a state-constrained optimal control one which allows the addition of different constraints on the dynamics of the moving sensor. In (Uciński & Chen, 2005), Uciński and Chen tried to properly formulate and solve the time-optimal problem for moving sensors observing the state of a DPS for optimal parameter estimation.

In (Uciński & Chen, 2006), the Turing's Measure of Conditioning is used to obtain optimal sensor trajectories. The problem is solved for heterogeneous sensors (i.e. with different measurement accuracies) in (Tricaud et al., 2008). Limited power resource is considered in (Patan et al., 2008). In (Song et al., 2005), realistic constraints to the dynamics of the mobile sensor are considered when a differential-drive mobile robot in the framework of the MAS-net (mobile actuator and sensor networks) Project (Chen et al., 2004).

The framework was further extended in (Tricaud & Chen, 2008a) where the problem of optimal actuation or excitation to increase the relevance of the observations and measurements of the states of a distributed parameter system was introduced. Using similar methodology, an optimal mobile actuation policy was found for a class of distributed parameter systems.

It is pinpointed in (Song et al., 2005) that one of the fundamental problems in DPS-parameter estimation using mobile sensors is that the optimal paths for the DPS-parameter estimation are conditional on the very parameters' values that yet have to be estimated and which are in fact unknown. Given parameters, how to optimally plan the motion trajectories of the mobile sensors has been known in the literature (Uciński, 2005 ; Patan, 2004), where the purpose of mobile sensing is to best estimate the parameters. Clearly, there is a "chick-and-egg" problem regarding the optimal mobile sensor motion planning and parameter estimation for distributed parameter systems.

Tricaud and Chen (Tricaud & Chen, 2008b), for the first time, solved this problem by proposing optimal interlaced mobile sensor motion planning and parameter estimation. The problem formulation is given in detail with a numerical solution for generating and refining the mobile sensor motion trajectories for parameter estimation of the distributed parameter system. The basic idea is to use the finite horizon control (HFC) type of scheme.

First, the optimal trajectories are computed in a finite time horizon based on the assumed initial parameter values. For the following time horizon, the parameters of the distributed parameter system are estimated using the measured data in the previous time horizon, and the optimal trajectories are updated accordingly based on these estimated parameters obtained. Simulation results are offered to illustrate the advantages of the proposed interlaced method over the non-interlaced techniques. We call the proposed interlaced scheme "on-line" or "real-time" which offers practical solutions to optimal measurement and estimation of a distributed parameter system when mobile sensors are used. It should be mentioned that this "on-line" problem has been recognized in the last chapter of (Patan, 2004) as an "extremely important" research effort.

In what follows, we first present the problem formulation for optimal sensor location for parameter estimation in distributed parameter systems as in (Uciński, 2005). In Section 3, we introduce our approach for solving optimal actuation problems. In Section 4, we describe the method used to reformulate the optimal location problems into optimal control ones. In Section 5, we describe our developed scheme solving the "chicken-and-egg" problem described earlier. Finally, in Section 6, we illustrate our methods by applying them to a distributed parameter system governed by a diffusive partial differential equation.

2. Optimal Measurement Problem

2.1 Problem Definition

Consider a distributed parameter system (DPS), a class of CPS, described by the partial differential equation:

$$\frac{\partial y}{\partial t} = \mathfrak{F}(\mathbf{x}, t, y, \boldsymbol{\theta}) \quad \text{in } \Omega \times T, \tag{1}$$

with initial and boundary conditions:

$$\mathfrak{B}(\mathbf{x}, t, y, \boldsymbol{\theta}) = 0 \quad \text{on } \Gamma \times T, \tag{2}$$

$$y = y_0 \quad \text{in } \Omega \times \{t = 0\}, \tag{3}$$

where $y(\mathbf{x}, t)$ stands for the scalar state at a spatial point $\mathbf{x} \in \bar{\Omega} \subset \mathbb{R}^n$ and time instant $t \in \bar{T}$. $\Omega \subset \mathbb{R}^n$ is a bounded spatial domain with sufficiently smooth boundary Γ, and $T = (0, t_f]$ is a bounded time interval. $\mathfrak{F}$ is assumed to be a known well-posed, possibly nonlinear, differential operator which includes first- and second-order spatial derivatives and includes terms for forcing inputs. $\mathfrak{B}$ is an known operator acting on the boundary Γ and $y_0 = y_0(\mathbf{x})$ is a given function.

We assume that the state y depends on the parameter vector $\theta \in \mathbb{R}^m$ of unknown parameters to be determined from measurements made by N static or moving pointwise sensors over the observation horizon T. We call $\mathbf{x}_s^j : T \to \Omega_{ad}$ the position/trajectory of the j-th sensor, where $\Omega_{ad} \subset \Omega \cup \Gamma$ is a compact set representing the domain where measurements are possible. The observations from the j-th sensor are assumed to be of the form:

$$z^j(t) = y(\mathbf{x}_s^j(t), t) + \varepsilon(\mathbf{x}_s^j(t), t), \quad t \in T, \quad j = 1, \ldots, N, \tag{4}$$

where ε represents the measurement noise which is assumed to be white, zero-mean, Gaussian and spatial uncorrelated with the following statistics:

$$E\left\{\varepsilon(\mathbf{x}_s^j(t), t)\varepsilon(\mathbf{x}_s^i(t'), t')\right\} = \sigma^2 \delta_{ji} \delta(t - t'), \tag{5}$$

where σ^2 stands for the standard deviation of the measurement noise, δ_{ji} and $\delta(.)$ are the Kronecker and Dirac delta functions, respectively.

With the above settings, similar to (Uciński, 2005), the optimal parameter estimation problem is formulated as follows: Given the model (1)–(3) and the measurements z^j from the sensors $\mathbf{x}_s^j$, $j = 1, \ldots, N$, determine an estimate $\hat{\theta} \in \Theta_{ad}$ (Θ_{ad} being the set of admissible parameters) of the parameter vector which minimizes the generalized output least-squares fit-to-data functional (Banks & Kunisch, 1989 ; Omatu & Seinfeld, 1989) given by:

$$\hat{\theta} = \arg \min_{\vartheta \in \Theta_{ad}} \sum_{j=1}^{N} \int_T \left[z^j(t) - y(\mathbf{x}_s^j(t), t; \vartheta) \right]^2 dt \tag{6}$$

where y is the solution of (1)–(3) with θ replaced by ϑ.

By observing (6), it is possible to foresee that the parameter estimate $\hat{\theta}$ depends on the number of sensors N and the mobile sensor trajectories $\mathbf{x}_s^j$. This fact triggered the research on the topic and explains why the literature so far focused on optimizing both the number of sensors and their trajectories. The intent was to select these design variables so as to produce best estimates of the system parameters after performing the actual experiment.

In order to achieve optimal sensor location, some quality measure of sensor configurations based on the accuracy of the parameter estimates obtained from the observations is required. Such a measure is usually related to the concept of the Fisher Information Matrix (FIM) (Sun, 1994), which is frequently referred to in the theory of optimal experimental design for lumped parameter systems (Fedorov & Hackl, 1997). Its inverse constitutes an approximation of the covariance matrix for the estimate of θ.

Let us write:

$$\mathbf{s}_s\left(t\right)=\left(\mathbf{x}_s^1\left(t\right),\ldots,\mathbf{x}_s^n\left(t\right)\right),\quad\forall t\in T, \tag{7}$$

and let $n=\dim\left(\mathbf{s}_s\left(t\right)\right)$. Given the assumed statistics of the measurement noise, the FIM has the following representation (Quereshi et al., 1980):

$$\mathbf{M}\left(\mathbf{s}_s\right)=\sum_{j=1}^{N}\int_T\mathbf{g}\left(\mathbf{x}_s^j\left(t\right),t\right)\mathbf{g}^T\left(\mathbf{x}_s^j\left(t\right),t\right)dt, \tag{8}$$

where

$$\mathbf{g}\left(\mathbf{x},t\right)=\nabla_{\vartheta}y\left(\mathbf{x},t;\vartheta\right)\big|_{\vartheta=\theta^0} \tag{9}$$

denotes the vector of the so-called sensitivity coefficients, θ^0 being a prior estimate to the unknown parameter vector θ (Uciński, 2000).

However, the FIM can hardly be used in an optimization as is. Therefore, it is necessary to maximize some scalar function Ψ of the information matrix to obtain the optimal experiment setup. The introduction of the scalar criterion allows us to pose the sensor location problem as an optimization problem. Several choices for such a function can be found in the literature (Atkinson & Donev, 1992; Fedorov & Hackl, 1997; Walter & Pronzato, 1997) and the most popular one is the D-optimality criterion defined:

$$\Psi\left(\mathbf{M}\right)=-\log\det\left(\mathbf{M}\right). \tag{10}$$

Its use yields the minimal volume of the uncertainty ellipsoid for the estimates of the parameters. In this chapter, only the D-optimality criterion is considered.

2.2 Sensor Model

We assume that the sensors are mounted on vehicles whose dynamics are described by the following equation:

$$\dot{\mathbf{s}}_s\left(t\right)=f\left(\mathbf{s}_s\left(t\right),\mathbf{u}_s\left(t\right)\right)\quad\text{a.e. on }T,\quad\mathbf{s}_s\left(0\right)=\mathbf{s}_{s0} \tag{11}$$

where the function $f:\mathbb{R}^n\times R^r\to\mathbb{R}^n$ is continuously differentiable; $\mathbf{s}_{s0}\in\mathbb{R}^n$ represents the initial position of the sensors, and $u_s:T\to\mathbb{R}^r$ is a measurable control function satisfying the following inequality:

$$\mathbf{u}_{sl}\le\mathbf{u}_s\left(t\right)\le\mathbf{u}_{su}\quad\text{a.e. on }T \tag{12}$$

for some constant vectors $\mathbf{u}_{sl}$ and $\mathbf{u}_{su}$. We assume that all the vehicles have to stay within an admissible region Ω_{ad} (a given compact set) where measurements are possible. Ω_{ad} can be conveniently defined:

$$\Omega_{ad}=\left\{\mathbf{x}\in\Omega:b_{si}\left(\mathbf{x}\right)=0,i=1,\ldots I\right\}, \tag{13}$$

where the b_{si} are known continuously differentiable functions. That is, the following constraints have to be satisfied:

$$h_{sij}\left(\mathbf{s}_s\left(t\right)\right)=b_{si}\left(\mathbf{x}_s^j\left(t\right)\right)\le0,\quad\forall t\in T, \tag{14}$$

where $1\le i\le I$ and $1\le j\le N$.

For simpler notation, we reformulate the conditions described in (14) in the following way:

$$\gamma_{sl}\big(\mathbf{s}(t)\big) \le 0, \quad \forall t \in T, \tag{15}$$

where γ_{sl}, $l = 1,\ldots,\nu$ tally with (14), $\nu = I \times N$.

It is possible to consider additional constraints on the path of each vehicle such as specific dynamics, collision avoidance and any other constrains. For example, we can restrict the minimum distance between the vehicles. Such constraint can be achieved by forcing the following condition:

$$\beta_{sij}\big(\mathbf{s}_s(t)\big) = R^2 - \big\|\mathbf{x}_s^i(t) - \mathbf{x}_s^j(t)\big\|^2 \tag{16}$$

where $1 \le i < j \le N$ and R is the minimum distance ensuring that the measurements taken by the sensors can be considered as uncorrelated, or ensuring that the vehicles will not collide each other during the experiment.

2.3 Problem Formulation

The optimal measurement problem consists in obtaining the steering of each mobile sensor, by minimizing the design criterion $\Psi(.)$ function of the FIMs of the form (8), which depend on the very trajectories of the sensors. Constraints (12) on the maximum admissible steering and state constraints (15) have to be satisfied. Initial sensors location $\mathbf{s}_{s0}$ will also be taken into account as a variable to be optimized in addition to the control function $\mathbf{u}_s$. The given problem can be reformulated as the following optimization: Find the pair $(\mathbf{s}_{s0}, \mathbf{u}_s)$ which minimizes the criterion:

$$J\big(\mathbf{s}_{s0}, \mathbf{u}_s\big) = \Psi\big[\mathbf{M}(\mathbf{s}_s)\big], \tag{17}$$

for all pairs of possible measurement:

$$P = \Big\{\big(\mathbf{s}_{s0}, \mathbf{u}_s\big)\big|\mathbf{u}_s : T \to \mathbb{R}^r \text{ is measureable}, \mathbf{u}_{sl} \le \mathbf{u}_s(t) \le \mathbf{u}_{su} \text{ a.e. on } T, \mathbf{s}_{a0} \in \Omega_{ad}^M\Big\} \tag{18}$$

subject to constraints (15).

A methodology to solve this problem will be given in Section 4.

3. Optimal Actuation Problem

Note that, besides the explicit design variables there exists an implicit one that is the forcing input in (1). Therefore, for given sensor trajectories, our interest in this chapter focuses on designing the optimal forcing input so as to get the most accurate parameter estimates.

The optimal actuation problem is very close to the optimal measurement problem in the sense that both use the sensitivity coefficients as a measure of the quality of the parameter estimation. However, both problems differ in the following ways:

- The optimal measurement problem assumes that the forcing input in (1) is known whereas the optimal actuation problem attempts to optimize trajectories of mobile actuators constituting part of the entirety of the forcing input.
- In the optimal actuation problem, the sensors positions/trajectories are known beforehand and are not optimized, although it could be done jointly which is left as our future research effort.

We believe that when both sensors and actuators are movable, our framework presented in this chapter can solve the "smart sniffing and spraying" problem as outlined in (Chen et al.,

2004) in a model-based style, that is, we now have a solid basis on addressing the hard research question on "where to sniffing and where to spraying".

3.1 Actuator Model

Let us introduce:

$$\mathbf{s}_a(t) = \left(\mathbf{x}_a^1(t), \mathbf{x}_a^2(t), \ldots, \mathbf{x}_a^M(t)\right), \tag{19}$$

where $\mathbf{x}_a^k : T \to \Omega_{ad}$ is the trajectory of the k-th actuator. We assume that the actuators are mounted on vehicles whose dynamics are described by the following equation

$$\dot{\mathbf{s}}_a(t) = f\left(\mathbf{s}_a(t), \mathbf{u}_a(t)\right) \quad \text{a.e. on } T, \quad \mathbf{s}_a(0) = \mathbf{s}_{a0}, \tag{20}$$

Where the function $f : \mathbb{R}^M \times \mathbb{R}^r \to \mathbb{R}^M$ is continuously differentiable, $\mathbf{s}_{a0} \in \mathbb{R}^M$ represents the initial position of the actuators, and $\mathbf{u}_a : T \to \mathbb{R}^r$ is the control function satisfying the following inequality

$$\mathbf{u}_{al} \le \mathbf{u}_a(t) \le \mathbf{u}_{au} \quad \text{a.e. on } T, \tag{21}$$

for some constant known vectors $\mathbf{u}_{al}$ and $\mathbf{u}_{au}$.

We assume that all the vehicles are confined within an admissible region Ω_{ad} (a given compact set) where the actuation is possible. Ω_{ad} can be conveniently defined:

$$\Omega_{ad} = \left\{x \in \Omega : b_{ai}(\mathbf{x}) = 0, i = 1, \ldots, I\right\}, \tag{22}$$

where the b_{ai} functions are known continuously differentiable functions. That is to say that the following constraints have to be satisfied:

$$h_{aik}\left(\mathbf{s}_a(t)\right) = b_{ai}\left(\mathbf{x}_a^k(t)\right) \le 0, \forall t \in T, \tag{23}$$

where $1 \le i \le I$ and $1 \le k \le M$. For simpler notation, we reformulate the conditions described in (23) in the following way:

$$\gamma_{al}\left(\mathbf{s}_a(t)\right) \le 0, \forall t \in T, \tag{24}$$

where γ_{al}, $l = 1, \ldots, \nu$ tally with (23), $\nu = I \times M$. It would be possible to consider additional constraints on the path of the vehicles such as specific dynamics, collision avoidance and any other constraints.

The actuation function for the k-th mobile actuator is assumed to have the following form:

$$\mathfrak{F}_k(\mathbf{x}, t) = \mathfrak{G}_k\left(\mathbf{x}, \mathbf{x}_a^k, t\right). \tag{25}$$

3.2 Problem Definition

To define the considered problem, we reformulate (1):

$$\frac{\partial y}{\partial t} = \mathfrak{F}(\mathbf{x}, t, y, \boldsymbol{\theta}) + \sum_{k=1}^{M} \mathfrak{F}_k(\mathbf{x}, t) \quad in\ \Omega \times T, \tag{26}$$

with initial and boundary conditions remain unchanged. $\mathfrak{F}$ may still include forcing input terms.

For the framework of optimal actuation, the FIM is given by the following new representation:

$$\mathbf{M}(\mathbf{s}) = \sum_{k=1}^{M} \int_T \mathbf{h}\left(\mathbf{x}_a^k(t), t\right) dt, \tag{27}$$

where for the *k*-th actuator:

$$\mathbf{h}\left(\mathbf{x}_a^k(t), t\right) = \sum_{j=1}^{N} \mathbf{g}\left(\mathbf{x}_a^k(t), \mathbf{x}_s^j(t), t\right) \mathbf{g}^T\left(\mathbf{x}_a^k(t), \mathbf{x}_s^j(t), t\right), \tag{28}$$

and

$$\mathbf{g}\left(\mathbf{x}_a^k(t), \mathbf{x}(t), t\right) = \int_T \nabla_\vartheta \left(y\left(\mathbf{x}(\tau), \tau; \vartheta\right)\right)\Big|_{\vartheta=\theta^0} d\tau. \tag{29}$$

In (29), y is the solution of (26) for $\mathfrak{F}_k(\mathbf{x}, \tau) = \mathfrak{G}_k\left(\mathbf{x}, \mathbf{x}_a^k, \tau\right)\delta(t - \tau)$ for all $k = 1, \ldots, M$.

The purpose of the optimal actuation problem is to determine the forces (controls) applied to each vehicle conveying an actuator, which minimize the design criterion $\Psi(.)$ defined on the FIMs of the form of (8), which are determined unequivocally by the corresponding trajectories, subject to constraints on the magnitude of the controls and induced state constraints. To increase the degree of optimality, our approach also considers $\mathbf{s}_{a0}$ as a control parameter vector to be optimized in addition to the control function $\mathbf{u}_a$.

Given the above formulation we can cast the optimal actuation policy problem as the following optimization problem: Find the pair $(\mathbf{s}_{a0}, \mathbf{u}_a)$ which minimizes

$$J(\mathbf{s}_{a0}, \mathbf{u}_a) = \Psi\left[\mathbf{M}(\mathbf{s}_a)\right] \tag{30}$$

over the set of feasible pairs

$$P = \left\{ (\mathbf{s}_{a0}, \mathbf{u}_a) \Big| \mathbf{u}_a : T \to \mathbb{R}^r \text{ is measureable, } \mathbf{u}_{al} \le \mathbf{u}_a(t) \le \mathbf{u}_{au} \text{ a.e. on } T, \mathbf{s}_{a0} \in \Omega_{ad}^M \right\} \tag{31}$$

subject to the constraints .

The solution to this problem can hardly have an analytical solution. It is therefore necessary to rely on numerical techniques to solve the problem. A wide variety of techniques are available (Polak, 1997). However, the problem can be reformulated as a classical Mayer problem where the performance index is defined only via terminal values of state variables.

4. Optimal Control Problem Reformulation

In this section, both problems from Sections 2 and 3 are converted into canonical optimal control ones making possible the use of existing optimal control problems solvers.

To simplify our presentation, we define the function $\text{svec} : \mathbb{S}^m \to \mathbb{R}^{m(m+1)/2}$, where $\mathbb{S}^m$ denotes the subspace of all symmetric matrices in $\mathbb{R}^{m \times m}$ that takes the lower triangular part (the elements only on the main diagonal and below) of a symmetric matrix $\mathbf{A}$ and stacks them into a vector $\mathbf{a}$:

$$\mathbf{a} = \text{svec}(\mathbf{A}) = \text{col}\left[\mathbf{A}_{11}, \mathbf{A}_{21}, \ldots, \mathbf{A}_{m1}, \mathbf{A}_{22}, \mathbf{A}_{32}, \ldots, \mathbf{A}_{m2}, \ldots, \mathbf{A}_{mm}\right]. \tag{32}$$

Reciprocally, let $\mathbf{A} = \text{Smat}(\mathbf{s})$ be the symmetric matrix such that $\text{svec}(\text{Smat}(\mathbf{a})) = \mathbf{a}$ for any $\mathbf{a} \in \mathbb{R}^{m(m+1)/2}$.

Consider the matrix-valued function:

$$\Pi_s\left(s_s(t),t\right) = \sum_{j=1}^{N} \mathbf{g}\left(\mathbf{x}_s^j(t),t\right)\mathbf{g}^T\left(\mathbf{x}_s^j(t),t\right), \tag{33}$$

for the optimal sensor trajectory problem, and the function:

$$\Pi_a\left(\mathbf{s}_a(t),t\right) = \sum_{k=1}^{M} h\left(\mathbf{x}_a^k(t),t\right), \tag{34}$$

for the optimal actuator trajectory problem.

Setting $r_x : T \to \mathbb{R}^{m(m+1)/2}$, x being s or a, as the solution of the differential equations:

$$\dot{\mathbf{r}}_x(t) = \mathrm{svec}\left(\Pi_x\left(\mathbf{s}_x(t),t\right)\right), \quad \mathbf{r}_x(0) = 0, \tag{35}$$

we can obtain:

$$\mathbf{M}(\mathbf{s}_x) = \mathrm{Smat}\left(\mathbf{r}_x\left(t_f\right)\right), \tag{36}$$

Minimization of $\Psi\left[\mathbf{M}(\mathbf{s}_s)\right]$ thus reduces to minimization of a function of the terminal value of the solution to (35). Introducing an augmented state vector:

$$\mathbf{q}_x(t) = \begin{bmatrix} \mathbf{s}_x(t) \\ \mathbf{r}_x(t) \end{bmatrix}, \tag{37}$$

we obtain:

$$\mathbf{q}_{x0} = \mathbf{q}_x(0) = \begin{bmatrix} \mathbf{s}_{x0} \\ \mathbf{0} \end{bmatrix}. \tag{38}$$

Then the equivalent canonical optimal control problem consists in finding a pair $(q_0, u) \in \overline{P}$ which minimizes the performance index:

$$\overline{J}\left(\mathbf{q}_{x0}, \mathbf{u}_x\right) = \phi\left(\mathbf{q}_x\left(t_f\right)\right) \tag{39}$$

subject to:

$$\begin{cases} \dot{\mathbf{q}}_x(t) = \phi\left(\mathbf{q}_x(t), \mathbf{u}_x(t), t\right) \\ \quad \mathbf{q}_x(0) = \mathbf{q}_{x0} \\ \quad \overline{\gamma}_{xl}\left(\mathbf{q}_x(t)\right) \le 0 \end{cases} \tag{40}$$

where:

$$\overline{P} = \left\{\left(\mathbf{q}_{x0}, \mathbf{u}_x\right) \middle| \mathbf{u}_x : T \to \mathbb{R}^r \text{ is measurable}, \mathbf{u}_{xl} \le \mathbf{u}_x(t) \le \mathbf{u}_{xu} \text{ a.e. on } T, \mathbf{s}_{x0} \in \Omega_{ad}^M\right\} \tag{41}$$

and

$$\phi(\mathbf{q}_x, \mathbf{u}_x, t) = \begin{bmatrix} f\left(\mathbf{s}_x(t), \mathbf{u}_x(t)\right) \\ \mathrm{svec}\left(\Pi_x\left(\mathbf{s}_x(t), t\right)\right) \end{bmatrix}, \tag{42}$$

$$\overline{\gamma}_{xl}\left(\mathbf{q}_x(t)\right) = \gamma_{xl}\left(\mathbf{s}_x(t)\right). \tag{43}$$

The above problem in canonical form can be solved using one of the existing packages for numerically solving dynamic optimization problems, such as RIOTS_95 (Schwartz et al. 1997), DIRCOL (Stryk, 1999) or MISER (Jennings et al., 2002). We choose RIOTS_95, which is designed as a MATLAB toolbox written mostly in C and runs under Windows 98/2000/XP and Linux. The theory behind RIOTS_95 can be found in (Schwartz, 1996).

5. Real-Time Interlaced-Scheme

5.1 Measurements and Parameters Estimation

Once the optimal trajectories have been computed, the measurements are done as described in Section 1. However, the observations are completed until the end of the finite horizon for which the trajectory was computed. Instead, after a fraction of the horizon, the data gathered so far are used to refine the estimation of the parameters values.

In order to determine refined values of the parameters, we use the Matlab command "lsqnonlin", a routine for solving non-linear least squares problems and especially for our case, the least squares fitting problems. "lsqnonlin" allows the user to incorporate his/her own function to compute. In our problem, the input of the function is a set of parameters as well as the measurements and the output is the error between the measurement and the simulated value of the measurement for the set of parameters.

$$\min_{\boldsymbol{\theta}} = \frac{1}{2} \sum_{i=1}^{N} f_i(\boldsymbol{\theta})^2 \tag{44}$$

with

$$f_i(\boldsymbol{\theta}) = z^i(t_0, \dots t_k) - \hat{y}\left(\mathbf{x}_s^i(t_0, \dots, t_k), t_0, \dots, t_k; \boldsymbol{\theta}\right). \tag{45}$$

Prior to the experiment, we determine the value of the state $\hat{y}(\mathbf{x}, t; \boldsymbol{\theta})$ for a set of parameter value $\boldsymbol{\theta} \in \Omega_{ad}$ in an offline manner. We assume that the state variations between two values of a parameter are linear enough to allow interpolation. Using this database obtained "offline" allows faster computation of the function to be called by the optimization algorithm.

5.2 The Interlaced Scheme

Let us summarize the interlaced strategy step by step:

1. Given a set of parameters $\hat{\boldsymbol{\theta}}$ for the DPS (its initial value being given prior to the first iteration), we design an optimal experiment, i.e., optimal trajectories for the mobile sensors to follow.

2. The sensors takes measurements along their individually assigned trajectories. Measurements are simulated taking the real value of the state along the trajectory and adding zero-mean white noise.

3. Measurement data are used to refine the estimate of the parameters using an optimization routine such as "lsqnonlin". The optimization routine computes the parameters such that the difference between the measurements and the simulated values of the state along the trajectory is minimized. Go back to Step-1.
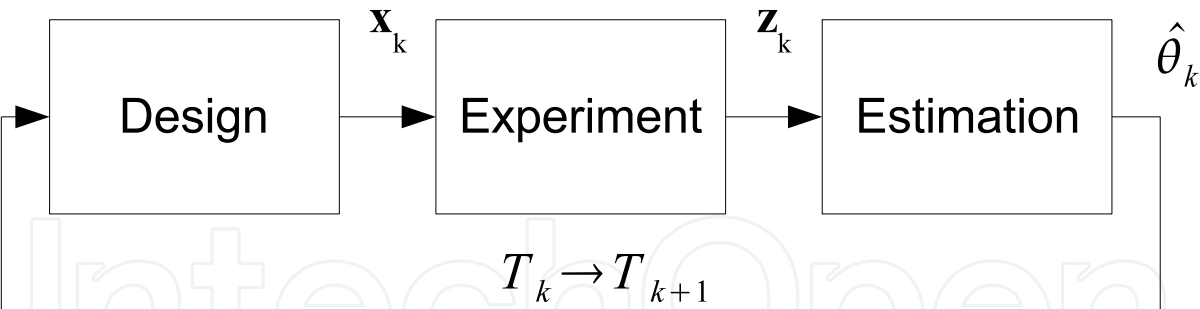
The above algorithm is illustrated in Figure 1.

Fig. 1. The interlaced scheme illustrated

6. An Illustrative Example

6.1 Optimal Sensor Trajectories (Offline Results)

The model used for a specific diffusion process is the same as in (Uciński, 2005) except that the parameter values are different. The considered system is governed by the following diffusive partial differential equation:

$$\frac{\partial y}{\partial t} = \nabla \cdot (\kappa \nabla y) + \mathfrak{F},$$
(46)

for $\mathbf{x} = [x_1, x_2]^T \in \Omega = (0,1)^2$ and $t \in [0,1]$, subject to homogeneous zero initial and Dirichlet boundary conditions. The spatial distribution of the diffusion coefficient is assumed to have the form:

$$\kappa(x_1, x_2) = \theta_1 + \theta_2 x_1 + \theta_3 x_2.$$
(47)

In our example, we select the initial estimates of the parameter values as $\theta_1^0 = 0.1$, $\theta_2^0 = 0.6$ and $\theta_3^0 = 0.8$, which are assumed to be nominal and known prior to the experiment. The forcing input $\mathfrak{F}$ is defined as:

$$\mathfrak{F}(\mathbf{x}, t) = 20 \exp\left(-50(x_1 - t)^2\right)$$
(48)

The sensitivity function is obtained "offline" or beforehand using the Matlab PDE Toolbox, prior to the function call of RIOTS by Matlab. The computation of the sensitivity function requires solutions of the followings equations:

$$\begin{cases} \dfrac{\partial y}{\partial t} = \nabla \cdot (\kappa \nabla y) + 20 \exp\left(-50(x_1 - t)^2\right) \\[2mm] \dfrac{\partial g_1}{\partial t} = \nabla \cdot \nabla y + \nabla \cdot (\kappa \nabla g_1) \\[2mm] \dfrac{\partial g_2}{\partial t} = \nabla \cdot (x_1 \nabla y) + \nabla \cdot (\kappa \nabla g_2) \\[2mm] \dfrac{\partial g_3}{\partial t} = \nabla \cdot (x_2 \nabla y) + \nabla \cdot (\kappa \nabla g_3) \end{cases}$$
(49)

where $\nabla = \partial/\partial x_1 + \partial/\partial x_2$. Note that there are three sensitivity equations since there are 3 parameters θ_1, θ_2, θ_3.

The dynamics of the mobile sensors follow the simple model:

$$\dot{\mathbf{x}}_s^j(t) = \mathbf{u}^j(t), \quad \mathbf{x}_s^j(0) = \mathbf{x}_{s0}^j \tag{50}$$

with additional constraints:

$$|\mathbf{u}(t)| \le 0.7, \quad \forall t \in T . \tag{51}$$

The optimal trajectories obtained are given in Figures 2 and 3. In Figure 2, all three sensors have fixed initial positions ($x_s^1(0) = (0.1, 0.1)$, $x_s^2(0) = (0.1, 0.5)$ and $x_s^3(0) = (0.1, 0.9)$). In Figure 3, sensors initial positions are left to be optimized too.

(a)   (b)
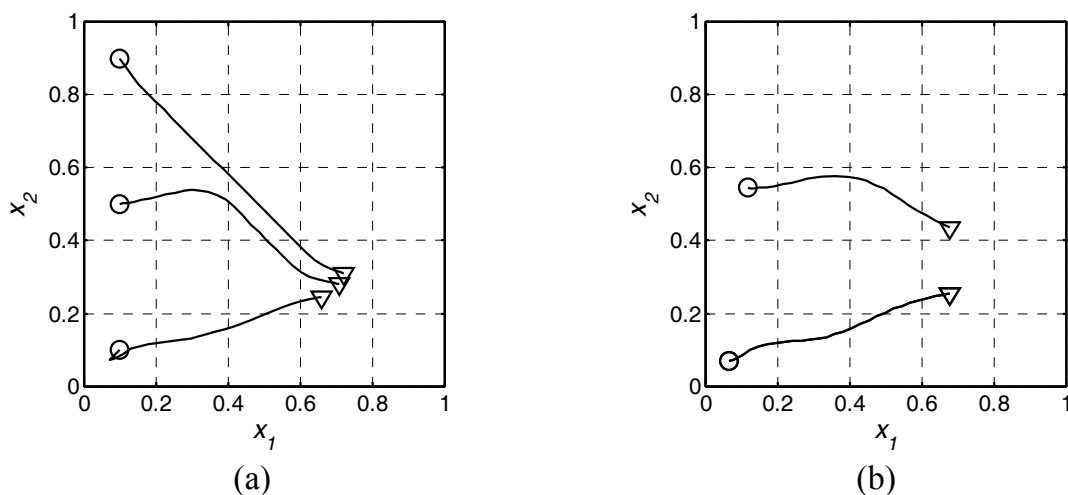
Fig. 2. (a): Optimal sensor trajectories with fixed initial positions, (b): Optimal sensor trajectories with optimal initial positions

It is important to mention that for Figure 2.(b), two sensors have the same trajectory. This result can be explained by the assumption that the noise is uncorrelated.

6.2 Optimal Actuator Trajectories

In this part, we use a similar example to illustrate our method. We consider the two-dimensional diffusion equation:

$$\frac{\partial y}{\partial t} = \nabla \cdot (\kappa \nabla y) + \sum_{i=1}^{M} \mathfrak{F}_i, \tag{52}$$

for $\mathbf{x} = [x_1, x_2]^T \in \Omega = (0,1)^2$ and $t \in [0,1]$, subject to homogeneous zero initial and Dirichlet boundary conditions. The spatial distribution of the diffusion coefficient is also assumed to have the form:

$$\kappa(x_1, x_2) = \theta_1 + \theta_2 x_1 + \theta_3 x_2. \tag{53}$$

In our example, we select the initial estimates of the parameter values as $\theta_1^0 = 0.1$, $\theta_2^0 = -0.05$ and $\theta_3^0 = 0.2$, which are assumed to be nominal and known prior to the experiment. The actuation function is defined:

$$\mathfrak{F}_i(\mathbf{x}, \mathbf{x}_a^i, t) = 1000 \exp\left(-50\left(\left(x_{a1}^i(t) - x_1\right)^2 + \left(x_{a2}^i(t) - x_2\right)^2\right)\right), \tag{54}$$

where $\mathbf{x}_a^i = [x_{a1}^i, x_{a2}^i]^T$. The dynamics of the mobile actuators follow the simple model:

$$\dot{\mathbf{x}}_a^j(t) = \mathbf{u}^j(t), \quad \mathbf{x}_a^j(0) = \mathbf{x}_{a0}^j \tag{55}$$

and additional constraints:

$$\left|\mathbf{u}(t)\right| \leq 0.7, \quad \forall t \in T . \tag{56}$$

Our goal is to design their trajectories so as to obtain possibly the best estimates of θ_1, θ_2 and θ_3.

The determination of the FIM follows the same way used in Section 4.1.

Five different given sensor configurations or setups are considered, and for each setup optimal actuation trajectories of different number of actuators (1, 2 and 3) are compared:

1. One static sensor located in the centre of the domain (0.5, 0.5),
2. One static sensor located near one of the corners of the domain (0.2, 0.8),
3. Three static sensors located throughout the domain ((0.1, 0.7), (0.5, 0.2), (0.6, 0.4)),
4. One moving sensor with a linear motion (0.1, 0.2) → (0.6, 0.7),
5. Two moving sensors. One moving sensor with a linear motion (0.1, 0.2) → (0.6, 0.7) and the other one moving along an arc.

Results for the different cases are summarized in Table 1, and the resulting trajectories can be observed in Figures 4-8. In the figures, static sensors locations are represented by a red **x**, mobile sensors trajectories are in red and actuator trajectories are in blue (○ locates the starting point and ∇ the ending point).

	Case 1	Case 2	Case 3	Case 4	Case 5
1 actuator	15.991	18.051	10.904	14.465	12.547
2 actuators	12.582	14.273	7.36	11.095	7.4806
3 actuators	11.28	13.022	5.8136	9.8976	6.4512

Table 1. Values of the D-optimality criterion $\Psi(\mathbf{M})$ for the different test cases
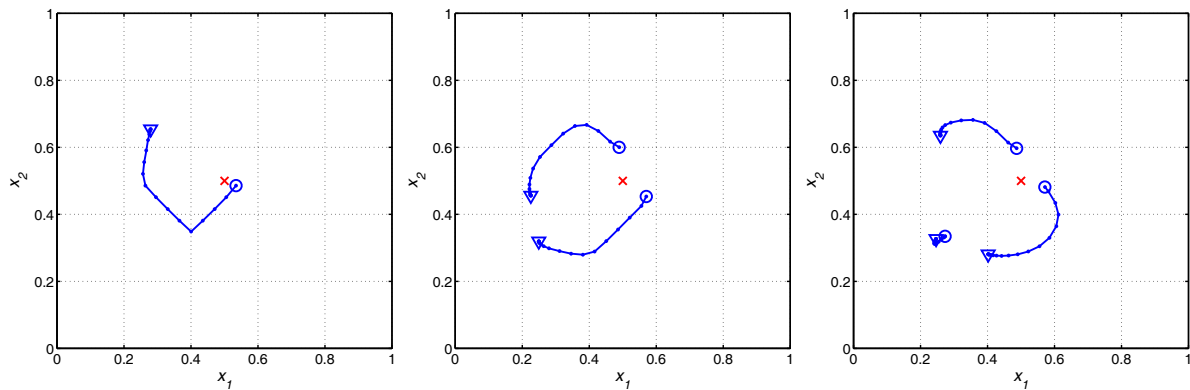
Fig. 4. D-Optimum trajectories of mobile actuators for one stationary sensor
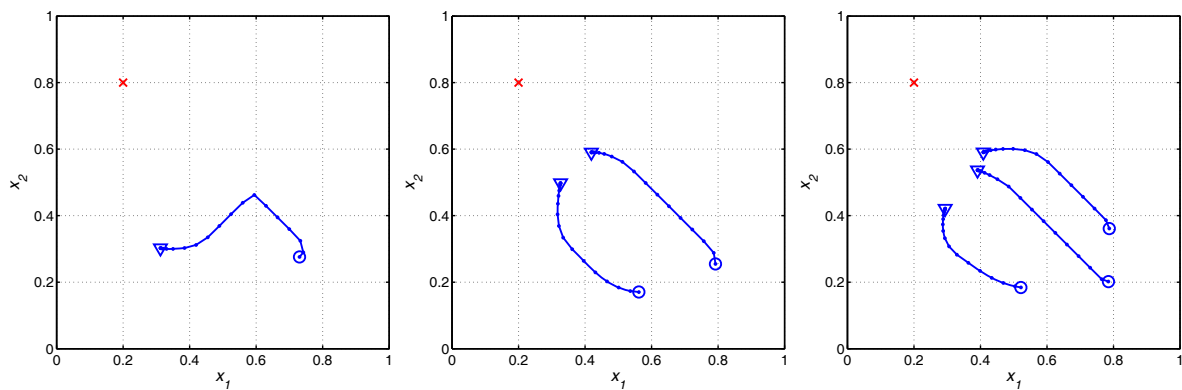
Fig. 5. D-Optimum trajectories of mobile actuators for one stationary sensor
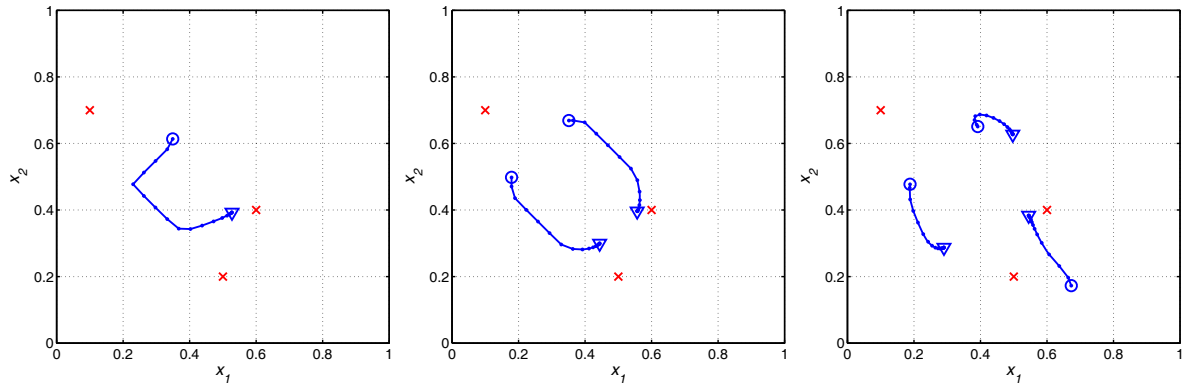
Fig. 6. D-Optimum trajectories of mobile actuators for three stationary sensors
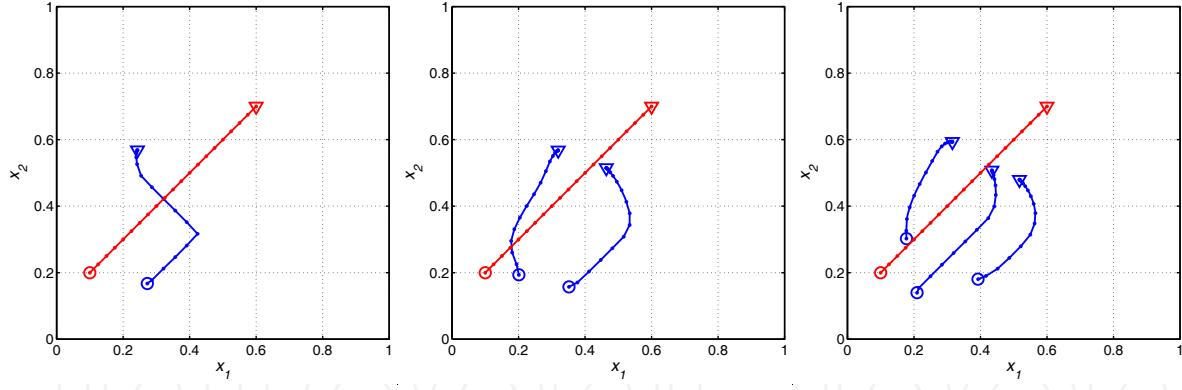
Fig. 7. D-Optimum trajectories of mobile actuators for one moving sensor
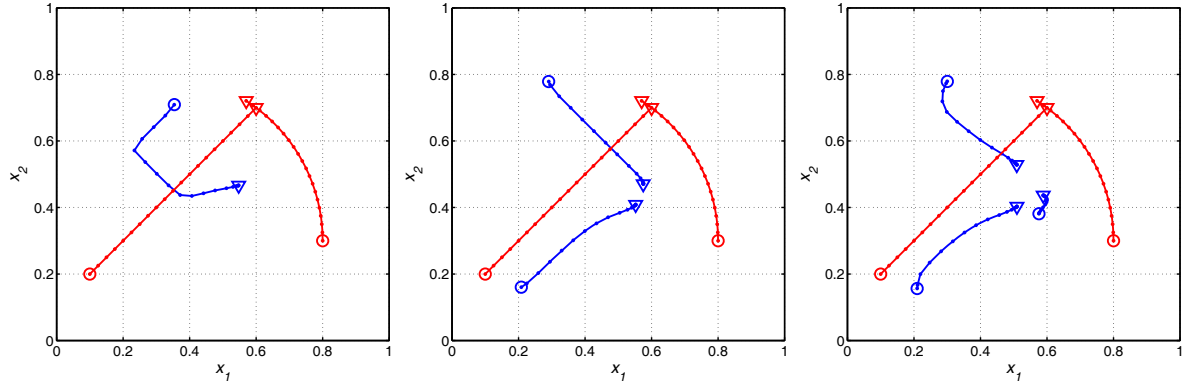

Fig. 8. D-Optimum trajectories of mobile actuators for two moving sensors

As expected, for all cases, the performance criterion value decreases as the number of actuator increases. We can also notice that both the mobility, population and location of the sensors have a direct impact on the performance of the strategy. Therefore, we can suppose the existence of an optimal combination of sensor and actuator trajectories.

6.3 Optimal Sensor Trajectories (Online Results)

In this section, we focus our attention on the performance of the online methodology described in Section 5. The experiment is run for different noise statistics and for each case results are given in the form of sensor trajectories and parameter estimates. For case 1, $\sigma = 0.0001$, for case 2, $\sigma = 0.001$, and for case 3, $\sigma = 0.01$. In all cases, we consider 3 mobile sensors. The control of the mobile sensors u is limited between -0.7 and 0.7. All three sensors have fixed initial positions ($x_s^1(0) = (0.1, 0.1)$, $x_s^2(0) = (0.1, 0.5)$ and $x_s^3(0) = (0.1, 0.9)$). The results for the previously defined case are respectively given in Figure 9. for Case 1, in Figure 10 for Case 2 and in Figure 11 for Case 3. For each figure, subfigure (a) gives the sensor trajectories, the evolution of the estimates is shown in (b) and the measurements are given in (c).
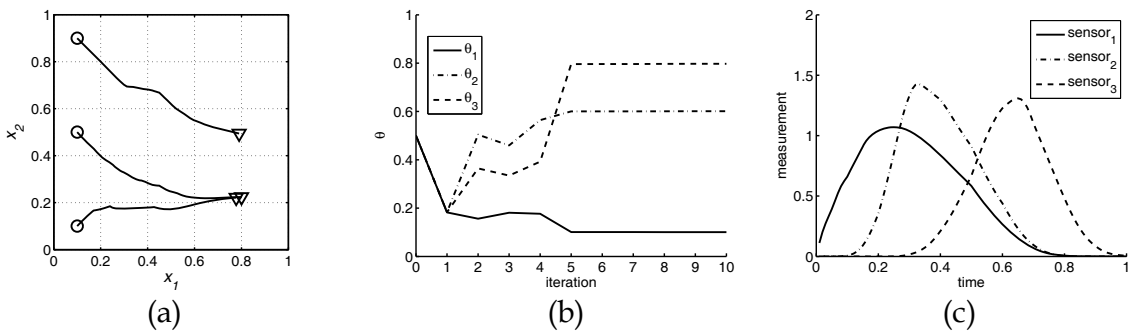
Fig. 9. Closed-loop D-Optimum experiment for $\sigma = 0.0001$. From left to right (sensor trajectories, parameter estimates and sensor measurements)
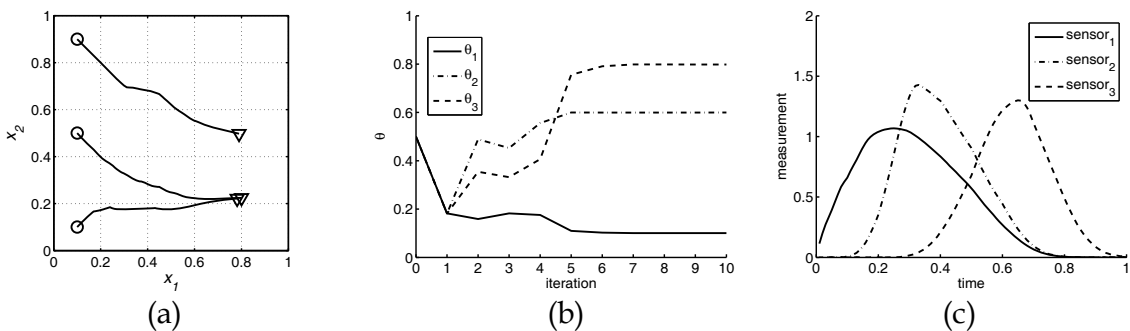
Fig. 10. Closed-loop D-Optimum experiment for $\sigma = 0.001$. From left to right (sensor trajectories, parameter estimates and sensor measurements)

(a)   (b)   (c)
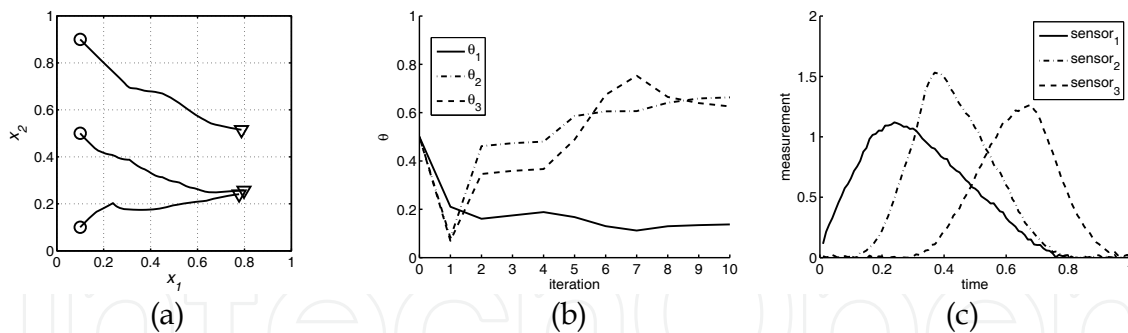
Fig. 11. Closed-loop D-Optimum experiment for $\sigma = 0.01$. From left to right (sensor trajectories, parameter estimates and sensor measurements)

From these figures, we have the following observations:

- In all the cases, the sensors have similar trajectories as they try to follow the excitation wave along the x_1 axis $20\exp\left(-50\left(x_1 - t\right)^2\right)$.

- For low noise amplitude (cases 1 and 2), the experiment is long enough to obtain good estimates of the parameters. In case 3, the experiment is not long enough to obtain convergence.

- In all cases, we can clearly observe that the trajectories of the mobile sensors change as the estimated values of the parameters are getting closer to the real values.

7. Conclusions

In this chapter, we described a numerical procedure for optimal sensor-motion scheduling of diffusion systems for parameter estimation. The state of the art problem formulation was presented so as to understand our contribution to the field. The problem was formulated as an optimization problem using the concept of the Fisher information matrix.

We then introduced the optimal actuation framework for parameter identification in distributed parameter systems. The problem was reformulated into an optimal control one.

Later, using our developed "online" scheme, mobile sensors find an initial trajectory to follow and refine the trajectory as their measurements allow finding a better estimate of the system's parameters. Using the Matlab PDE toolbox for the PDE system simulations, RIOTS_95 Matlab toolbox for solving the optimal path-planning problem and Matlab Optimization toolbox for the estimation of the system's parameters, we were able to solve this parameter identification problem in an interlaced manner successfully.

With the help of the Matlab PDE toolbox for the system simulations and RIOTS_95 Matlab toolbox for solving the optimal control problem, we successfully obtained the optimal solutions of all the introduced methods for illustrative examples. We believe, this chapter has for the first time laid the rigorous foundation for real-time estimation for a class of cyber-physical systems (CPS).

8. Future Work

Our future efforts will go towards combining all of the techniques described here into a single framework. Obtaining optimal trajectories for both moving actuators and moving sensors is a challenging but very exciting research topic.

It should be emphasized that the "online" estimation methodology sets the basis for exciting future research. Indeed, we can now investigate problems related to communication between mobile nodes such as time-varying information sharing topology, communication range, information loss and other well-known problems in the scope of task-oriented mobile multi-agent systems.

9. Acknowledgements

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**Mobile Robots - State of the Art in Land, Sea, Air, and
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Since the introduction of the first industrial robot Unimate in a General Motors automobile factory in New
Jersey in 1961, robots have gained stronger and stronger foothold in the industry. In the meantime, robotics
research has been expanding from fix based robots to mobile robots at a stunning pace. There have been
significant milestones that are worth noting in recent decades. Examples are the octopus-like Tentacle Arm
developed by Marvin Minsky in 1968, the Stanford Cart crossing a chair-filled room without human assistance
in 1979, and most recently, humanoid robots developed by Honda. Despite rapid technological developments
and extensive research efforts in mobility, perception, navigation and control, mobile robots still fare badly in
comparison with human abilities. For example, in physical interactions with subjects and objects in an
operational environment, a human being can easily relies on his/her intuitively force-based servoing to
accomplish contact tasks, handling and processing materials and interacting with people safely and precisely.
The intuitiveness, learning ability and contextual knowledge, which are natural part of human instincts, are
hard to come by for robots. The above observations simply highlight the monumental works and challenges
ahead when researchers aspire to turn mobile robots to greater benefits to humankinds. This book is by no
means to address all the issues associated mobile robots, but reports current states of some challenging
research projects in mobile robotics ranging from land, humanoid, underwater, aerial robots, to rehabilitation.

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