Deployment strategies of mobile sensors for monitoring of mobile sources: method and prototype

Conference Paper · June 2015

DOI: 10.13140/RG.2.1.1724.7844

Alban Vergnaud
University of Angers

Thanh Phong TRAN
University of Angers

Laetitia Perez
Polytech Angers Angers France

Laurent Autrique
University of Angers

A. Vergnaud, T.P. Tran, L. Perez, P. Lucidarme, L. Autrique, *Deployment strategies of mobile sensors for monitoring of mobile sources: method and prototype*, Control Architectures of Robots 2015, Lyon, France, June 2015.

Deployment strategies of mobile sensors for monitoring of mobile sources: method and prototype

Alban VERGNAUD[1], Thanh Phong TRAN[1], Laetitia PEREZ[2], Philippe LUCIDARME[1], Laurent AUTRIQUE[1]

[1] LABORATOIRE ANGEVIN DE RECHERCHE EN INGENIERIE DES SYSTEMES, 62 AVENUE NOTRE DAME DU LAC, 49000 ANGERS, FRANCE.
Corresponding author: *alban.vergnaud@univ-angers.fr*

[2]LTN-UMR CNRS 6607, UNIVERSITE DE NANTES
LA CHANTRERIE, RUE CHRISTIAN PAUC, BP50609, 44306 NANTES CEDEX 03, FRANCE

Abstract: *In this communication, the characterization of mobile sources is studied. A quasi online identification method based on the iterative regularization of ill-posed inverse problem is proposed in order to monitor an evolutionary phenomenon. Several strategies related to sensors choice (adaptive selection of relevant sensors within the fixed network or mobile sensors management) are discussed. To illustrate the investigated approaches, an experimental prototype has been developed in the context of thermal sciences. The experiment is described: design, characterization, exchanges protocols for signals acquisition, movement of mobile elements (sources and sensors).*

Keywords: inverse problem, parametric identification, thermal process, conjugate gradient method, experimentation.

I. INTRODUCTION

The distributed parameters identification (continuously depending on space and time) in systems described by nonlinear partial differential equations (PDE) is, in general, difficult. A widely used approach is to minimise an output error cost-function. The minimization of a quadratic criterion describing the difference between outputs predicted by the mathematical model and observed outputs collected by using sensors is an inverse problem [1].

In more specific context of thermal sciences, inverse problems of heat conduction studied to identify properties, heat flows or initial conditions, are usually ill-posed [2]. In fact, the stability condition (in Hadamard's sense [1]) is generally not satisfied since weak disturbances on measurements generate large variations on the identified parameters. This can be shown from a matrix point of view where assembled matrices obtained by finite element method [3] (for the numerical solution of partial differential equations system) are ill-conditioned.

Matrices inversion is not relevant in the presence of measurements uncertainties [4-5]. In this context, Tikhonov has developed methods allowing the construction of stable solutions [1-2, 6]. These methods are generally called as "regularization method ". The main principle is to formulate a new problem considering an additional parameter (the regularization parameter) such that the new problem is stable. The construction of these new problems is not trivial. Among various existing approaches, the conjugate gradient method [7] allowing the iterative minimization of the output error has a regularisation property in the context of inverse problems of heat conduction.

Indeed, this method leads to solve iteratively three well posed problems [8]. In [2], Alifanov says: "*such a method of damping the instability when specifying an approximate solution for an ill-posed problem is based on viscous properties of numerical algorithms of optimization*". This stabilizing effect is illustrated in [9] for an academic situation corresponding to a 1D geometry for which analytical solutions are available. It is highlighted that the main structure of the unknown parameter is identified from early iterations. The Conjugate gradient algorithm behaves as a filter able to reject disturbances on measurements during the iterative process of minimization. The number of iteration is often considered as the regularization parameter of these methods. This inverse problem resolution is traditionally implemented offline: identification begins when all data are collected [10-13]. However recent adaptations have shown its potential for a quasi-online use in a numerical context [14]. To illustrate the interest of this new approach in a real situation, experimentation was designed for the identification of heating mobile sources. This main objective of the prototype is to estimate the trajectory and the heating of one or more surfacic heating sources from temperature measurements. For quasi online identification, the problem of optimum selection of sensors can be posed. Two strategies are discussed in this paper: the first concerns the selection quasi-online of most relevant localized sensors within a network of sensors, the second is devoted to intelligent movement strategies for several mobile sensors.

In the following, the complete description of the experimental device is presented. The choice of dimensions and materials are justified. Heat sources are detailed and the acquisition of collected data is presented. Heat elements and sensors are embedded on several mobile robots (Khepera III) and the procedure is detailed. The methodology for the identification is presented and the innovative aspects (procedure quasi-online, strategies of sensors choice) are explained. Finally, conclusions and outlooks are briefly trained.

II. EXPERIMENTAL DEVICE

In this part, the studied thermal situation is described. It is intended to illustrate the quasi online resolution of an inverse problem of heat conduction using the iterative regularization of the conjugate gradient method. It also allows testing strategies of sensors choice (positioning, deployment).

A. Field of study

Mobile heating sources are moving on a square plate. In this study, the hypothesis of a 2D geometry was considered in order to reduce the computing times. This assumption is valid only if heat transfers in the plate thickness are neglected. Then, a thin metallic plate (with a high thermal conductivity) is considered. Aluminum plate was chosen (square plate with a size equal to 3m) and horizontally set on a support providing insulation.

In order to verify that the heat transfers can be neglected on the thickness plate, two mathematical models were compared. The first system (1) corresponds to the 2D assumption : the temperature $\theta(x,y;t)$ in each point (x,y) of the plate Ω and at every moment $t \in T$ satisfied:

$$\begin{cases} \forall(x,y;t)\in\Omega\times T & \rho c\dfrac{\partial\theta}{\partial t}-\lambda\Delta\theta=\Phi \\ \forall(x,y)\in\Omega & \theta(x,y;0)=\theta_0 \\ \forall(x,y;t)\in\partial\Omega\times T & -\lambda\dfrac{\partial\theta(x,y;t)}{\partial\vec{n}}=0 \end{cases} \quad (1)$$

where ρc is the volumetric heat capacity in $\mathrm{J.m^{-3}.K^{-1}}$, λ is the thermal conductivity in $\mathrm{W.m^{-1}.K^{-1}}$, θ_0 in K is the room temperature (equal to that of the surrounding medium), $\vec{n}$ is the normal unit vector at the border $\partial\Omega$. The flux Φ corresponds to the surface heat sources ϕ_{heat} and takes into account a convective exchange with the upper face of the plate as well as a perfect insulation on the lower face.

$$\Phi(x,y;t)=\frac{\phi_{heat}(x,y;t)-h\big(\theta(x,y;t)-\theta_0\big)}{e}$$

where h is the convective heat transfer coefficient in $\mathrm{W.m^{-2}.K^{-1}}$ and $e=2$ mm is the plate thickness.

System (2) corresponds to the aluminum plate (9 m^2) set on the insulating support, thickness $e_r=4.5$ cm, based on Rockwool panels, mono-density, semi-rigid, covered with a vapor barrier kraft polyethylene (reference is Rockwool-Rockmur-Kraft). The mathematical model describes the heat transfer in 3D geometry is the following:

$$\begin{cases} \forall(x,y,z;t)\in\Omega\times T & \rho c\dfrac{\partial\theta}{\partial t}-\lambda\Delta\theta=0 \\ \forall(x,y,z)\in\Omega & \theta(x,y;0)=\theta_0 \\ \forall(x,y,z;t)\in\partial\Omega_{lat}\times T & -\lambda\dfrac{\partial\theta}{\partial\vec{n}}=0 \\ \forall(x,y,z;t)\in\partial\Omega_{sup}\times T & -\lambda\dfrac{\partial\theta}{\partial\vec{n}}=-e\Phi \\ \forall(x,y,z;t)\in\partial\Omega_{inf}\times T & -\lambda\dfrac{\partial\theta_p}{\partial\vec{n}}=\dfrac{1}{R}(\theta-\theta_0) \end{cases} \quad (2)$$

where $\partial\Omega_{lat}$ is the lateral surface of the aluminum plate and $\partial\Omega_{sup}$ (resp. $\partial\Omega_{inf}$) the upper (resp. lower) face. Coefficient R is the thermal resistance of surface, also called thermal insulation coefficient of surface (in $m^2.K.W^{-1}$). In order to consider whether the assumption of 2D heat transfer is valid, temperatures predicted by the models (1) and (2) are compared for a set of realistic parameters indicated in table I.

TABLE I

PARAMETERS OF MODELS (1) AND (2) ACCORDING TO IS UNITS

$\rho c = 2.4\ \ 10^6$	$\lambda = 237$	$h = 15$	$R = 1.2$
$\phi_{heat}(x,y;t) = 10^5\, e^{-10^3 d^2} \sin\left(\dfrac{2\pi t}{1200}\right)$			$\theta_0 = 291$

In table I, $d(x,y)$ is the distance between the point (x,y) and the center of the upper face of the aluminum plate. It may be noted that the configuration 3D of this study is axisymmetric. The systems of partial differential equations (1) and (2) are solved by using the finite element method [3] implemented by the Comsol code interfaced with Matlab. On figure 1, the evolutions of temperature in various points of the superior face of the plate are proposed.

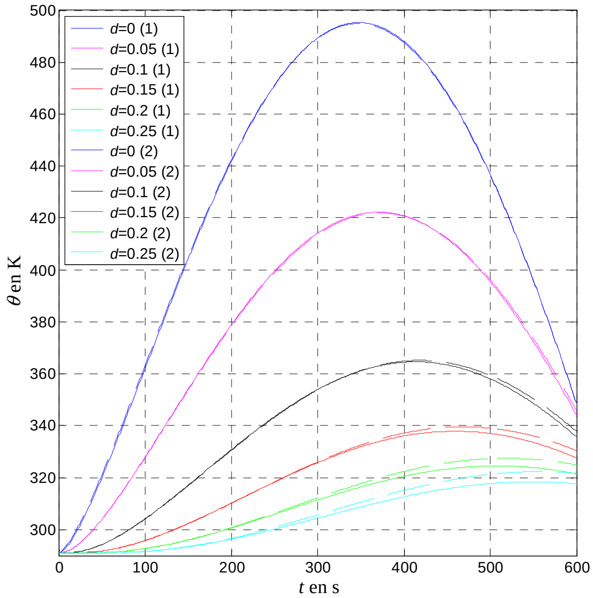


Fig. 1. Comparison of the 2D and 3D models.

Figure 1 shows that the 2D model is very satisfactory for points near the heating source. For points far away from the source, weak errors of model are obtained. The following table indicates in various points the mean absolute error between two models e_1, as well as the absolute average deviation of temperature e_2 between 2 points located on both sides of the plate (information obtained with the model (2)).

TABLE II

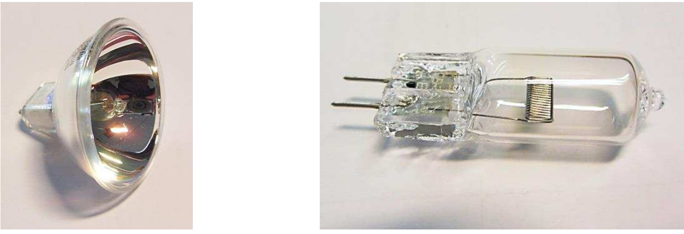
COMPARISONS BETWEEN TWO MODELS

d	0 cm	5 cm	10 cm	15 cm	20 cm
e_1	0.5 K	0.5 K	0.5 K	0.8 K	1.2 K
e_2	0.3 K	0.02 K	0.003 K	0.002 K	0.001 K

Considering figure 1 and table II, the assumption of the two-dimensional transfers is considered valid for an aluminum plate of 2mm thickness set on Rockwool panels (thickness 4.5cm). The mass of such a plate of $9\,m^2$ is slightly lower than 50 kg.

B. The heat sources

Heating sources without contact were chosen in order to avoid the inherent problems due to movements of the mobile sources. They are halogen lamps Philips of two different types (24V, 250W, GX5.3) and (36V, 400W, GY6.35), driven by programmable power supplies.



24V, 250W, GX5.3 36V, 400W, GY6.35

Fig. 2. Heating sources.

These lamps provide radiative heating $\phi_{heat}(x,y;t)$ with a temporal component adjusted by the power supply (delay inherent in the filament heating is neglected compared to the experimentation duration which is about 30 minutes and to the known dynamics of the thermal system). Thus, it is justified to consider for each source $\phi_{heat}(x,y;t)=\phi(t)\,f(x,y)$ where $\phi(t)$ is function of the power provided by the power supply and $f(x,y)$ is the spatial distribution of the heat flux density on the plate. Identification campaigns are required to know these parameters. The function $f(x,y)$ depends on halogen lamp properties and on the distance to the plate. A reflector located behind the lam increases the radiative flux received by the plate. If a uniform flux on a limited surface is desired then a kaleidoscope (optical device for homogenizing the flux) can be used; see an application in [15]. For such optical homogenizer, distance between the plate and the heat source is fixed (equal to the length of the kaleidoscope). In general cases, it is crucial to identify the spatial distribution $f(x,y)$. It is easy (using infrared thermography) to ensure that heating is axisymmetric. Thus heating flux spatial distribution $f(d)$ is identified where $d(x,y)$ is the distance between the point (x,y) and the center of the heating source. Without losses of the generalities, we can suppose that $f(d)$ can be written as continuous piecewise linear function and proceed a simultaneous identification of $f(d)$ and ϕ (for several powers) using calibrated experimentations associated with the conjugate gradient method [4]. This must be done for various distances between the source and the plate.

C. Sensors

For the temperature measurements, pyrometers were chosen in order to obtain observations without contact (which avoid intrusive effects and facilitate the sensors displacement).

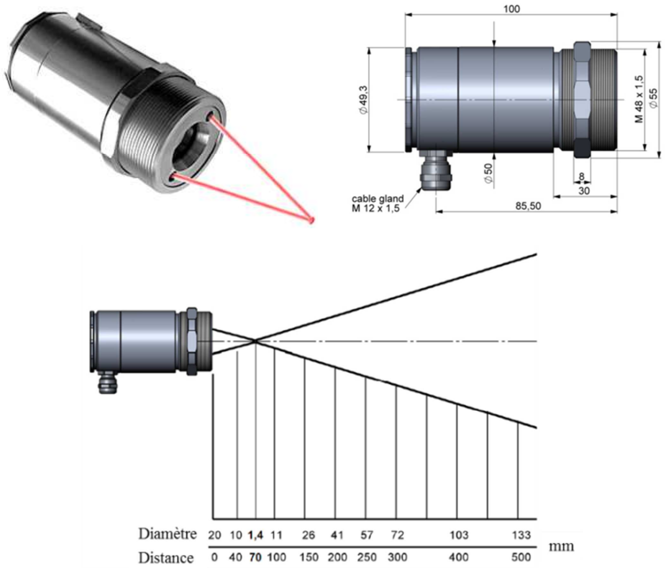


Fig. 3. Pyrometer Optris® CSlaser-LT-CF1.

Pyromers reference is Optris® CSlaser-LT-CF1 delivering an output current in the range 4-20mA. The temperature range is [273,773] in K. Each pyrometer is a cylinder approximately 10 cm long and 5 cm in diameter for a mass of 600g. The temperature resolution is 0.1K, the accuracy of 1% and the response time (at 90%) is 150ms. The measurement distance between the pyrometer and the plate is 7cm and the diameter of the measuring disk (corresponding to 90% of the emitted radiation) is 1.4mm.

D. Robots

In order to move the sources and the sensors, Khepera-III robots have been selected. These are designed by the Swiss Federal Institute of Technology in Lausanne and developed by the K-TEAM company. The diameter of each robot is 13cm and its height is 7cm. They are able to move a mass lower than 2kg at a maximum speed of 50cm/s. The autonomy is 8 hours (at constant speed and without the embedded platform Korebot-II) while the duration of the experimental campaigns will beabout 30 minutes.

The robots are connected to the management computer via a wireless router (wifi router) through which they can exchange information (frames) using the TCP/IP protocol (client/server).

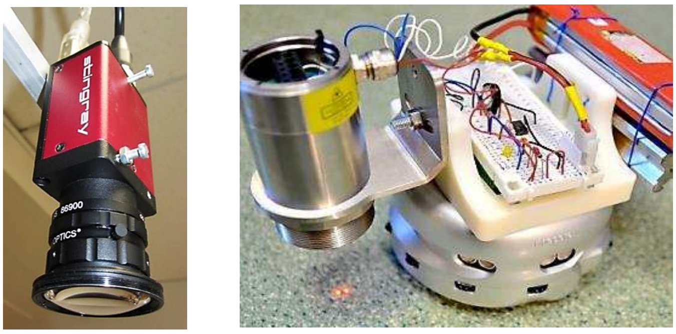


Fig. 4. Camera and Khepera-III robot equipped with a pyrometer.

Robots have various sensors (10 infrared sensors, 5 ultrasonic telemeters) and wheels with incremental encoders which allow knowledge about their relative positions but biases are encountered. In order to obtain the accurate position of each robot, a visible camera (camera AVT StingrayFireWire, F-046C, field of view 61.9° – 76.7°) is connected with the management computer. This camera has 780x580 pixels and an acquisition frequency at 55Hz. Using the software SSL-vision [16-17], the robots trajectories on the plate is registered and the coordinates as well as the robots orientations are sent to the management computer. This software uses the images provided by the camera and detects markers previously recorded (figure 5). These are used as a unique identifier; by setting a marker on each robot, it is possible to know its position (x_0, y_0) and its orientation (α_0) in a frame of a vector space Oxy. Once the new coordinates calculated, they are compared with the odometric measurements of the robots in order to estimate as well as possible the coordinates of the best robots on the plate. By using the camera, the accuracy of the robots position is about one centimeter.

For each robot equipped with a pyrometer, the temperature is measured and the analogical values (currents) are processed by a digital analogical converter (integrated in I/O card KoreIO connected on the expansion card). Then robot sends a frame to the management computer (by using the protocol TCP/IP client/server) containing the position, the temperature and the measured time

E. In practice…

The temperatures as well as the accurate positions of the robots are measured every second. The robots embedding the heating sources can move continuously.

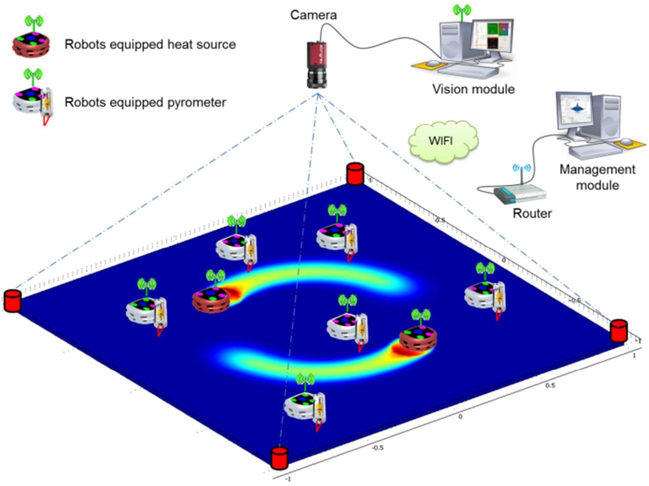


Fig. 5. Experimental device..

The robots embedding the pyrometers move according to the provided indications provided every ten seconds by the management computer (possibly connected to a second computer dedicated to the resolution of the identification problem).

Communication protocol TCP/IP (Transmission Control Protocol/Internet Protocol) is currently the most used in the local area networks and Internet between 2 programs or 2 machines (a client and a server). The TCP layer ensures that all data sent is received by the receiving machine. The protocol of data exchange between the client and the server via the sockets (interfaces of connection) networks TCP/IP is modeled figure 6.

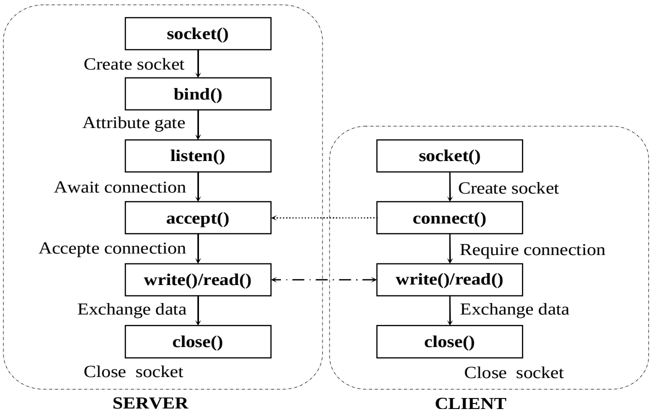


Fig. 6. Communication protocol TCP/IP.

The wireless router is the only link between robots, vision device and intelligent control (see figure 5). It manages the connection of the robots to the management module (devoted to mobile sensors and mobile sources) and to the parametric identification module. These various elements have each one a unique IP address. These elements open a socket of listening and expect a request for connection coming from another device. When a third machine tries to be connected to the host machine it activates connection and the dialogue between the two machines is set up. Data is exchanged in the form of data frames which are specifically coded.

After measure treatments and process of quasi online identification (see paragraph III), each robot receives a frame of data which contains its current coordinates (x_0, y_0), its current orientation (α_0) and the desired position (x_1, y_1). Then, it calculates a trajectory to move from the current position (x_0, y_0, α_0) to the desired position (x_1, y_1), avoiding obstacles (if any).

III. IDENTIFICATION

In the following the methodology for heating flux identification is briefly exposed.

A. Direct problem

When all the parameters of the model are known $P = \{\Omega, T, \rho, c, \lambda, h, \phi_{heat}, \theta_0\}$, partial differential equations system (1) is solved in order to obtain the temperature evolution $\theta(x, y; t)$ at any point of the plate and at every moment. This problem is called a well-posed problem because few noises on parameters P introduce small disturbances on state estimation $\theta(x, y; t)$. Once a parameter is unknown, an inverse problem is considered in order to proceed with its identification.

B. Inverse problem

In this communication, heat flux density is considered unknown and temperature measurement $\hat{\theta}_i(t)$ are performed with several mobile sensors i. In order to estimate the unknown parameter, a method based on the minimization of the output error is implemented. The principle of this resolution is to find a value of unknown parameter $\phi_{heat}(x, y; t)$ that minimizes the difference between predicted and real outputs. The following estimator is proposed:

$$\phi^*_{heat} = \text{Arg}\min\left(\frac{1}{2}\sum_{i=1}^{N}\int_{\mathcal{T}}\left(\theta(C_i, t, \phi_{heat}) - \hat{\theta}_i(t)\right)^2 dt\right) \qquad (3)$$

where N is number of sensors C_i and $\mathcal{T}$ the time interval during which measures are taken into account.

In following paragraphs, sensor choice (fixed or mobile) strategies are considered and the definition of the intervals of observations $\mathcal{T}$ is discussed.

C. The conjugate gradient method (Offline method)

In order to minimize the cost function defined in (3), the iterative Conjugate Gradient Method (CGM) is implemented [7]. An application to thermal engineering is presented in [8] and its regularization properties are illustrated in [9]. The selected algorithm is solving iteratively three well posed problems on the considered time interval :

- direct problem (1) corresponding to the estimated heat flux density ϕ_{heat} at iteration k and computation of the criterion (3).
- adjoint problem (4) according to Lagrangian formulation in order to compute the gradient of the cost function and the descent direction at iteration k .
- sensitivity problem (5): calculation of the sensitivity function defined as the variation of temperature induced by variation of the heat flux density (in the descent direction).

At the end of the resolution of these three problems, a new value of ϕ_{heat}^{k+1} is calculated.

For the adjoint problem (4), $E(x,y;t)$ depends on the difference between the estimated temperature and measurements at sensor position. This problem is retrograde in time ($\tau = t_f$ which is the end of the time interval).

$$\begin{cases} \forall(x,y;t)\in\Omega\times\mathfrak{T} & \rho c\dfrac{\partial\psi}{\partial t}+\lambda\Delta\theta = E+\dfrac{2h\psi}{e} \\ \forall(x,y)\in\Omega & \theta(x,y;\tau)=0 \\ \forall(x,y;t)\in\partial\Omega\times\mathfrak{T} & -\lambda\dfrac{\partial\psi(x,y;t)}{\partial\vec{n}}=0 \end{cases} \qquad (4)$$

Sensitivity problem is formulated as follows:

$$\begin{cases} \forall(x,y;t)\in\Omega\times\mathfrak{T} & \rho c\dfrac{\partial(\delta\theta)}{\partial t}-\lambda\Delta(\delta\theta)=\delta\Phi^k \\ \forall(x,y)\in\Omega & (\delta\theta)(x,y;0)=0 \\ \forall(x,y;t)\in\partial\Omega\times\mathfrak{T} & -\lambda\dfrac{\partial(\delta\theta)(x,y;t)}{\partial\vec{n}}=0 \end{cases} \qquad (5)$$

Variation of the heat flux density used in sensitivity problem is:

$$\delta\Phi^k = \frac{\left(\delta\phi_{heat}^k\right)-2h(\delta\theta)}{e}$$

Problems (4) and (5), gradient and descent depth formulation are explained in [5, 12-14]. The iterative process continues until the cost function (3) is lower than the admissible level of minimization [2]:

$$J_{stop} = \frac{1}{2}n\sigma^2 \qquad (6)$$

where n is number of measurements C_i considering on time interval $\mathfrak{T}$ and σ the standard deviation of the noise measurements (assumed as a Gaussian profile with mean value equal to zero).

This method is offline when $\mathfrak{T} = \left[0, t_f\right]$, the identification process begins only when all measurement are collected. It is thus necessary to wait the end of the experiment to identify the trajectory and power of heating sources.

D. Adaptation for a quasi-online method

For identification during the process, when measurements are available online, the previous method could be adapted. It's possible to consider a set of time interval $\mathfrak{T}_j \subset T$ as $\bigcup \mathfrak{T}_j = T$.

The choice of these sliding time intervals (start, length, recovery rates), is explained in [14] where several strategies are presented. Techniques for online identification are based on the behavior of the minimization algorithm to handle compromises between quality of the estimate and delay between estimation and measurements.

Algorithm is started only if new observations are not in adequacy with predicted temperature evolution. Lengths of time intervals must be chosen considering the dynamics of the experimentation (priori experimental knowledge can be taken into account). Knowledge on the physical system studied is an undeniable asset to 'adjust' the online procedure.

In the considered situation, it is shown that offline identification leads to results 70 minutes after the end of the experiment of 10 minutes, the online method provides satisfactory results only 1 minute after the end. This approach also allows estimation of the unknown parameter even before the end of the process (the average difference between the measurements and the results of online method is about 30 seconds).

E. Choice of relevant sensors.

In order to identify heating fluxes, a network of fixed sensors can be considered. On the investigated square plate (9m²), it is obvious that several sensors are not sensitive to sources displacement. Thus the problem concerns the selection of a few "relevant" sensors within a large number of "blind" sensors.

In [19], methods based on the optimal design of experiments are presented. In general, these approaches require a priori knowledge of a nominal value for the unknown parameter. The method proposed below is based on analysis of the iteratively solved sensitivities functions (5).

On the time interval $\mathcal{T}$ the sensors with sufficient sensitivity are selected (an example inspired by this approach is presented in [20]). Let us consider for example that 4 relevant sensors have to be selected. A possible strategy is to divide the interval $\mathcal{T}$ into 4 subintervals $\mathcal{T}^i$ of equal length, and on each, selected the sensor with the best sensitivity (norm sense) $L^2\left(\mathcal{T}^i\right)=\int_{\mathcal{T}^i}\left(\delta\theta\left(x,y;t\right)\right)^2 dt$. This should ensure enough informative signals on the collected data during $\mathcal{T}$. The previous method can be performed offline $\left(\mathcal{T}=T\right)$ or on sliding time intervals $\left(\mathcal{T}_j\subset T\right)$. An illustration of this method is proposed below for identification the heat flux density of a mobile heating source moving in thin plaque (1m²) with an offline CGM. Noisy measurements are available from 16 fixed sensors. In order to reduce the influence of noise measurement on the cost function J_{stop} (6), 4 least relevant sensors are rejected during the iterative process based on norm $L^2\left(\mathcal{T}^i\right)$. In Fig 7, is presented, 12 sensors (at different iterations) used to estimate the unknown heat flux density.

The choice of the most relevant sensors during the iterative process of minimization is not based on priori information. It is based on the results of the identification and more specifically on the analysis of the sensitivity functions (in the descent direction $\delta\Phi^k$); see problem (5).

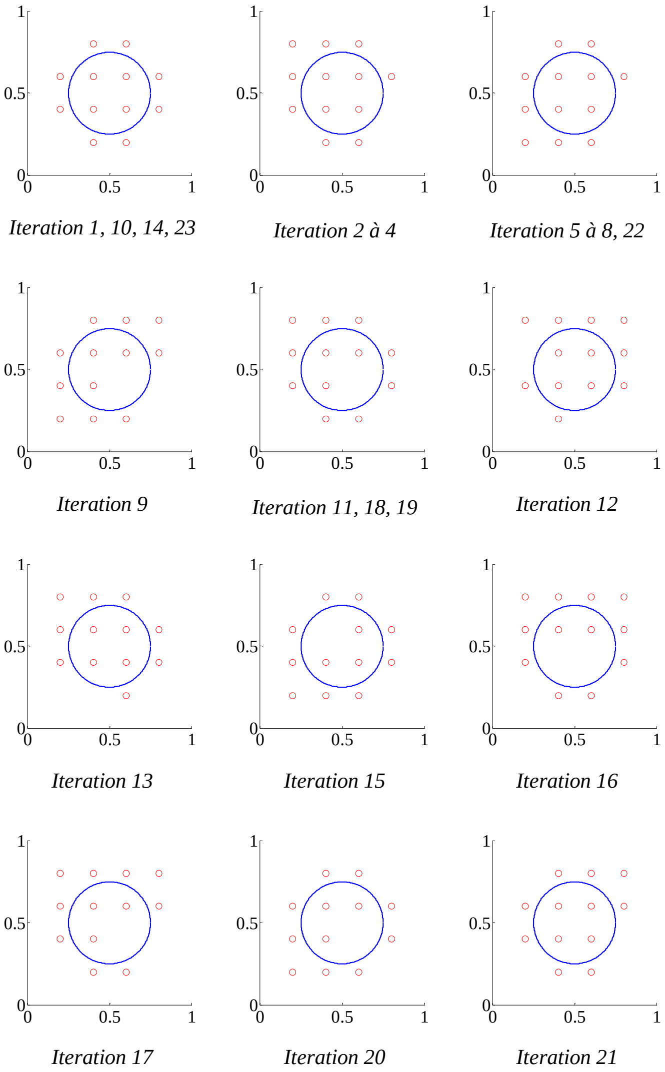


Fig. 7: Choice of sensors with offline method.

At each iteration of the minimization algorithm, it is easy to estimate the relevant spatial areas in time and select sensors. The initialization of the 12 sensors among 16 (see iteration 1) is made to cover the plate without a priori.

In figure 7, according to the iterations and directions preferred by the CGM algorithm, several less relevant sensors are rejected. It is quite attractive that this method requires no a priori information such as sensors selection techniques [19] that are based on an expected nominal location near unknown configuration. The estimation of the heat flux density are presented in Fig. 8.

The results of the identification obtained with 12 sensors (and presented figure 8) are reliable. In 23 iterations, the average residue between calculated and measured temperature is equal to -5.10^{-3} K.

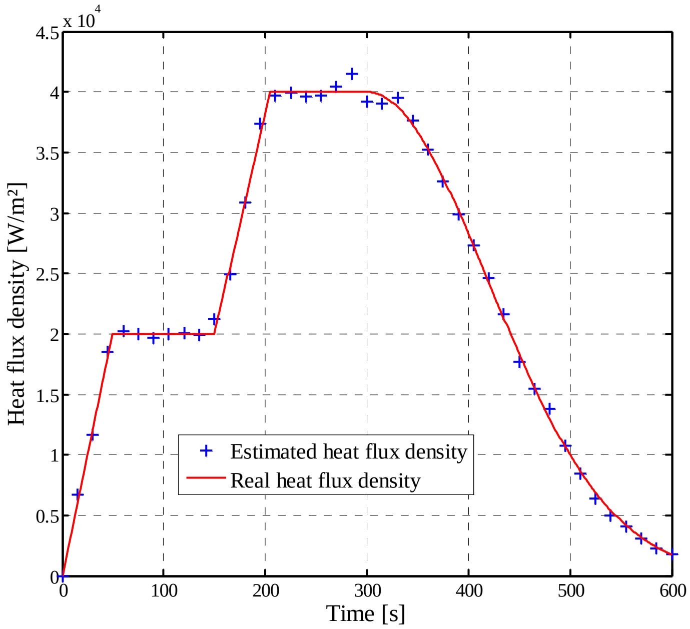


Fig. 8. Heat flux density identification at iteration 23.

Standard deviation of residues is equal to 0.48 K (which is of the order of magnitude of noise). The duration of identification on a standard laptop is about 40 minutes.

This concept can be used in strategies of mobile sensors deployment.

III. Concluding remarks and outlooks

A complete methodology (experimentation, definition of the inverse problem, resolution offline and online) is presented in this communication in order to investigate several strategies for mobile sources tracking observation. Where the system state is described by parabolic partial differential equations system (such as in heat equation), the selection of the relevant sensors within a fixed network or the definition online of the trajectories of mobile sensors is discussed.

The prospects envisaged at the end of this work consist in the realization of many experimental campaigns and to the study of non-linear systems for which input parameters depends on the system state (for example thermal conductivity is temperature dependent for large temperature variation)

This work was partly funded with ANR-12-BS03-008-03.

References

[1] Isakov V. *Inverse problems for Partial Differential Equations*. Ed. Springer-Verlag, New York, 1998.

[2] Alifanov O.M. *Inverse heat transfer problems*. Ed. Springer-Verlag, Berlin, 1994.

[3] Pepper D.W. and Heinrich J.C., *The finite element method – basic concepts and applications*, Ed. Taylor & Francis, New York, 2006.

[4] Abou Khachfe R. *Résolution numérique de problèmes inverses 2D non linéaires de conduction de la chaleur par la méthode des éléments finis et l'algorithme du gradient conjugué- Validation expérimentale*Thesis of the University of Nantes, LTN, Polytech-Nantes, 2000.

[5] Beddiaf S. *Identification paramétrique de systèmes d'EDP paraboliques non linéaires en géométrie 3D par une méthode de régularisation itérative*, Thesis of the University of Angers, LARIS, 2013.

[6] Morozov V.A. *Methods for solving incorrectly posed problems*. Ed. Springer-Verlag, New York, 1994.

[7] Minoux M. *Programmation mathématique – théorie et algorithmes.* Seconde édition, Ed. Tec&Doc Lavoisier, Paris, 2008.

[8] Jarny Y., Ozisik M.N. and Bardon J.P. (1991). *A general optimization method using adjoint equation for solving multidimensional inverse heat conduction*, International journal of heat and mass transfer, vol. 34, pp. 2911-2919, 1991.

[9] Prud'homme M. and Hung Nguyen T. *On the iterative regularization of inverse heat conduction problems by conjugate gradient method.* International Communications in Heat and Mass Transfer, vol. 25, n° 7, pp. 999-1008, 1998.

[10] Autrique L. and Serra J.J. *On the implementation of a finite element method for parameter identification*. First Conference on finite element applications, *LUXFEM*, Luxembourg, 13-14 November 2003.

[11] Perez L., Autrique L. and Gillet M. *Implementation of a conjugate gradient algorithm for thermal diffusivity identification in a moving boundaries system.* Journal of physics: Conf. Series, vol. 135, 2008.

[12] Beddiaf S., Perez L., Autrique L. et Jolly J.C. *Simultaneous determination of time-varying strength and location of a heating source in a three-dimensional domain.* Inverse Problems in Science and Engineering, vol. 22, n° 1, pp. 166-183, 2014.

[13] Beddiaf S., Perez L., Autrique L. and Jolly J.C. *Parametric identification of a heating mobile source in a three-dimensional geometry*. Inverse Problems in Science and Engineering, vol. 23, n° 1, pp. 93-111, 2015.

[14] Vergnaud A., Perez L. and Autrique L. *On-line monitoring of surfacic mobile heating sources.* International Conference on Inverse Problems in Engineering, Cracow, Poland, 12-15 May 2014.

[15] A. Vergnaud, L. Perez, P. Lucidarme, L. Autrique, *DARC-EDP: Conception du prototy*pe, Quatrièmes Journées des Démonstrateurs en Automatique, (Angers, France, Juin 2013).

[16] Martinez-Gomez L.A. et Weitzenfeld A., *Real Time Vision System for a Small Size League Team*, Proceedings of the 1st IEEE Latin American Robotics Symposium, (Mexico city, Mexico, 28-29 Octobre 2004).

[17] S. Zickler, T. Laue, O. Birbach, M. Wongphati et M. Veloso, *SSL-Vision: The Shared Vision System for the RoboCup Small Size League*, *RoboCup 2009: Robot Soccer World Cup XIII,* Springer, (2009), 425-436.