IDENTIFICATION OF DISTRIBUTED PARAMETER SYSTEMS BASED ON MULTIVARIABLE ESTIMATION AND WIRELESS SENSOR NETWORKS

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Abstract: One of the important problem related to the usage of wireless sensor networks in harsh environments is the identification of the states of the physical variables in the field, based on the measurements provided by the sensors. The sensor networks allow the usage of the multivariable estimation techniques in distributed parameter systems. The paper presents an application of a multivariable auto-regression estimation technique for identification in distributed parameter systems, based on a sensor network. A case study was presented for identification in a heat diffusion process.

1 INTRODUCTION

Sensor networks have proved their huge viability in the real world in a variety of domains. Advances in miniaturization, decreasing of their cost and power and improvements in wireless networking and micro-electro-mechanical systems have led to research for large-scale deployment of wireless sensor networks and formation of a new computing domain. In the last years the deployment of small-scale sensor networks in support of a growing array of applications has become possible (Akyildiz, 2002), (Chong, 2003).

The distributed parameter systems are systems whose state space is infinite dimensional. An object whose state is heterogeneous has distributed parameters. Partial differential equations are used to formulate problems involving functions of several variables, such as the propagation of sound or heat, electrostatics, electrodynamics, fluid flow, elasticity (Kubrusly, 1977).

Wireless sensor networks are extremely distributed systems having a large number of independent and interconnected sensor nodes, with limited computational and communicative potential. The sensor networks consist of hundreds or thousands of heterogeneous disposable sensor nodes, capable of sensing their environment and communicating with each other via wireless channels, coordinating and monitoring large areas. Individually nodes possess properties such as functionality and inter-node cooperation, under limited energy reserves and technological limitations. There are applications where the sensors were generally bulky devices wired to a central control unit whose role was to collect, process, and act upon the data gathered by individual sensors. A network of sensors could be developed with small motion detectors, metal detectors, pressure detectors, and vibration detectors, deployed around a valuable asset.

The paper (Volosencu, 2008) presents a recent survey of some characteristics of the sensor networks, distributed parameters systems and identification techniques, with examples of applications of modeling of distributed systems in sensor networks and identification based on multivariable identification with auto-regression and neural networks.

A strategy by which sensor nodes detect and estimate non-localized phenomena such as boundaries and edges (e.g., temperature gradients, variations in illumination or contamination levels) is study in (Novak, 2003).

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2 PROPOSED METHOD

The following assumptions related to the sensor network are made. The sensor network architecture has a number of base stations deployed in the field. Each base station forms a cell around itself that covers part of the area. Mobile wireless nodes and other appliances can communicate wirelessly. The base station, acting as a controller and as a key server, is assumed to be a laptop class device and supplied with long-lasting power. Different sensor network architectures may be used in practical applications (Akyildiz, 2002), (Chong, 2003). For a possible architecture some assumptions related to the sensor nodes may be done. All the sensors are similar in their computational and communication capabilities and have enough memory to store up to hundreds of bytes of data. The sensors may be static and only the access points may be mobile. Each sensor node knows its own location, even if they were deployed by scattering or physical installation. In a specific case the nodes can obtain their location with location evaluation methods, after deployment (Fig. 1).

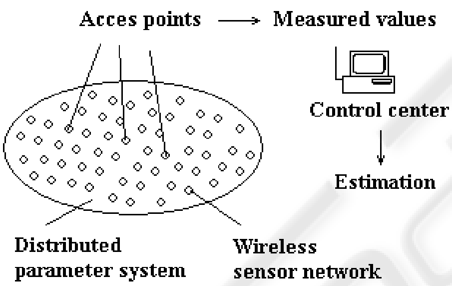

Figure 1: Sensor network.

The information from different sensors is built on the fact that actual sensor value is related with past values provided by the same sensor. This approach is based on a mathematical model that can predict the value of one sensor by taking into consideration the past and present values of neighbouring sensors or of the implied sensor itself. The computation implied in this approach is done at the base station level. The proposed technique relies on the fact that a sensor node is identified in the moment that he starts to send data, using a linear autoregressive multivariable predictor. The present method considers that a multivariable autoregressive (AR) model can efficiently approximate the time evolution of the measured values provided by each and every sensor within the coverage area. The AR model definition is:

$$x(t) = A_1 x(t-1) + \ldots + A_n x(t-n) + \xi(t) \qquad (1)$$

where x(t) is a vector of the series under investigation (in our case is the series of values measured by the sensors from the network):

$$x = \begin{bmatrix} x_1 & x_2 & \ldots & x_m \end{bmatrix}^T \qquad (2)$$

and A_i are the matrix of auto-regression coefficients, n is the order of the auto-regression and ξ is a vector containing the noise components that is almost always assumed to be a Gaussian white noise. By convention all the components $x_1(t),\ldots,x_n(t)$ of the multivariable time series x(t) are assumed to be zero mean. If not, another term (A_0) is added in the right member of equation (1). Based on the model (1), (2) the coefficients A_i may be estimated in case that the time series x(t), x(t-1),…,x(t-n) is known (recursive parameter estimation), either predict future value $\hat{x}(t)$ in case that A_i coefficients and past values x(t-1),…, x(t-n) are known (AR prediction). The method uses the time series of measured data provided by each sensor and relies on an autoregressive multivariable predictor placed in base stations (Fig. 2).

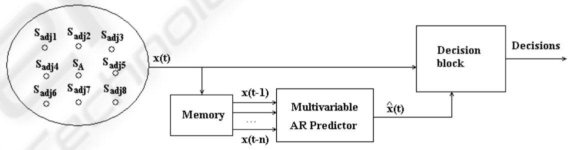

Figure 2: Multivariable AR prediction.

The principle is the following: a sensor node will be identified by comparing its output value x(t) with the value $\hat{x}(t)$ predicted using past/present values provided by the same sensor. The proposed methodology is described as follows. After this initialisation, at every instant time t the estimated value $\hat{x}_A(t)$ is computed relying only on past values $x_A(t-1)$, …, $x_A(0)$. First the parameter matrixes A_i are estimated using a recursive parameter estimation method. There are a large number of methods for obtaining AR coefficients (Ljung, 1999). An Armax method, with zero coefficients for the inputs is used. Second, the prediction value $\hat{x}(t)$ is obtained using the following equation:

$$\hat{x}_A(t) = A_1 x_A(t-1) + \ldots + A_n x_A(t-n) + \xi(t) \qquad (3)$$

After that, the present value $x_A(t)$ measured by the sensor node may be compared with its estimated value $\hat{x}_A(t)$ by computing the error:

$$e_A(t) = |x_A(t) - \hat{x}_A(t)| \qquad (4)$$

If this error is higher than the threshold ε_A the sensor A may be considered a potentially corrupted sensor. There is no simple method to establish the correct model order n in case of an AR model. Two parameters can influence the decision: the type of data measured by sensors and the computing limitations. Because both of them are a priori known, an off-line methodology is proposed. Realistic values are between 3 and 6.

3 CASE STUDY

Let us consider a distributed parameter system, described by a differential equation with partial derivatives, for example the propagation of a temperature wave in a homogenous planar field. Several sensor nodes $S_{i,j,}$ i=1,…,N and j=1,…,M, parts of a sensor network, are deployed in the system. These sensors are measuring the local variable (temperature θ [^{o}C]). A regression model that estimates the temperature value provided by the sensor S_A $\hat{x}_A(t) = \hat{\theta}_A(t)$ by taking into consideration the previous values of the data provided by sensor x_A(t-1), x_A(t-2),…, x_A(t-n) is developed, with n chosen correlated to the above consideration. The time distribution of the temperature θ through the homogenous medium in space is described by the equation:

$$\theta = \theta(z,t) \qquad (5)$$

where $\theta(z,t)$ is the temperature at the moment t, at distance z from the heat source. The heat conduction is described by the heat equation (Ljung, 1994):

$$c_\theta \frac{\partial^2}{\partial z^2}\theta(z,t) = \frac{\partial}{\partial t}\theta(z,t) \qquad (6)$$

where c_θ is the heat conductivity coefficient of the medium. In order to investigate how the method works, the function $\theta = \theta(z,t)$ is sampled into the aggregates $\theta_{j,k}$ (temperature value provided by $S_{j,k}$) situated at the distance $z_{j,k}$ from the origin. The energy conservation is governed for each point in the field by the following equation:

$$\frac{d}{dt}W_{j,k} = P_{in}^{j,k} - P_{out}^{j,k} \qquad (7)$$

where $W_{j,k}$ is the energy stored in point (j,k), $P_{in}^{j,k}$ is the input power in the point and $P_{out}^{j,k}$ is the output power from the point. The space model of the sensor deployed in the field with the heat sources is presented in Fig. 3.

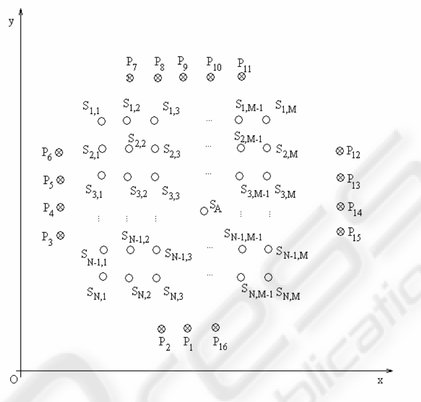

Figure 3: The deployment of the sensors.

Let the heat capacity of each point be denoted C and the heat transfer coefficient between the points $K_i^{j,k}$. These give the equation in time of the heat diffusion:

$$\frac{d}{dt}C\theta^{j,k}(t) = \sum_{i1} K_{i1}^{j,k}[\theta_{i1}^{j,k}(t) - \theta^{j,k}(t)] - \\ -\sum_{i2} K_{i2}^{j,k}[\theta_{i2}^{j,k}(t) - \theta^{j,k}(t)] \qquad (8)$$

A discrete time equivalent equation of (8), with a chosen adequate sample period *h* is used. Each cell of sensors may receive inputs from the around medium, from *r* sources with powers P_i, *i*=1, …, *r*, positioned around the network. The procedure is as follows. 1. The input data for estimation was a pseudo random binary signal for the powers *P*. The output of the heat diffusion model *x* at these signals was computed. Means and trends of the signals were removed. The signals were filtered. The input P_1 and the output x_1 in this case are presented in Fig. 4.

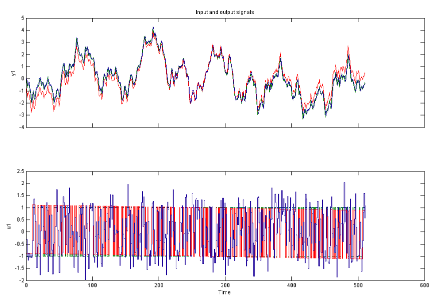

Figure 4: The input-output estimation data.

2. A set with a multivariable model with 9 state space equation for the cell and n=8 time delays for the estimate was chosen. 3. The criterion of selected the model was the residual from Fig. 5 and the fit of the estimate in the simulation.

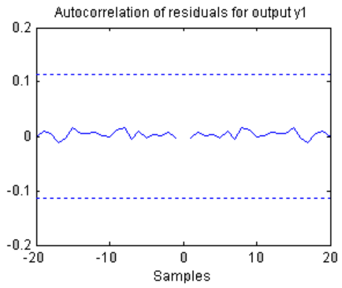

Figure 5: Residuals.

The multivariable estimation model with auto-regression has 9x9x9=729 parameters which are majority 0 and only on the diagonals of the 9 parameter matrix are nonzero values. For example, the parameters of the estimation model for x_A are given in equation (9).

$$\begin{aligned}\hat{x}_A(t) &= 1{,}207x_1(t-h) - 0{,}302x_2(t-2h) + \\ &+ 0{,}079x_1(t-3h) - 0{,}026x_1(t-4h) + \\ &+ 0{,}019x_1(t-5h) - 0{,}0286x_1(t-6h) + \\ &+ 0{,}022x_1(t-7h) - 0{,}0112x_1(t-8h) + \\ &+ e(t)\end{aligned} \tag{9}$$

Four cases of travelling wave temperatures may be taken in consideration, when four travelling temperature waves pass on the North, South, West and East sides of the cell, next to the sensor cell, as it is presented in Fig. 2. For the North travelling temperature wave the signal diagram of powers is presented in Fig. 6.

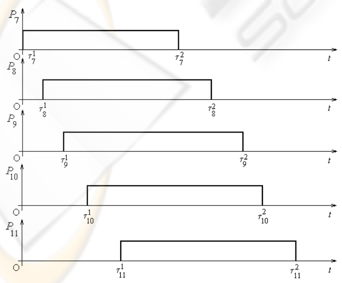

Figure 6: A set of power test signals.

The response in temperature diffusion is presented in Fig. 7. The estimation model may generalize in the cases that the waves are passing through diagonal face to the cell. When the error $e_A(t)$ at the sensor S_A passed over the threshold ε_A, imposed by the user, a decision must be taken.

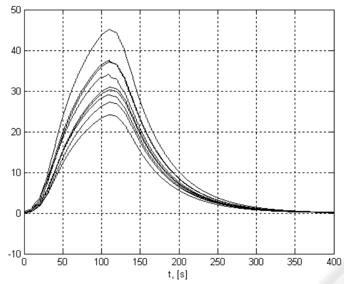

Figure 7: The time response of the sensors, that fit the estimate.

4 CONCLUSIONS

A multivariable method for identification of distributed parameter systems based on sensor networks is proposed based on an auto-regression method with the values provide by the sensor network. A case study was presented in a heat diffusion process. An estimation model is developed based on input-output data and residuals. The estimation model was tested using travelling heat waves. Being localized on a base station level, with a reduced amount of computation the method is suitable even for large-scale sensor networks.

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