Interpolation Techniques for Spatial Distributed System Identification Using Wireless Sensor Networks

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Abstract: - Wireless sensor networks (WSNs) being an assembly of hundreds or thousands of sensor nodes, each with sensing (temperature, humidity, sound level, light intensity, magnetism, etc.) and wireless communication capabilities, provide vast opportunities for monitoring and mathematical modeling the spatial information about a region of interest. Starting from the measurements collected by sensor nodes inside an investigated spatial distributed system, this paper offers a view upon the use of two interpolation techniques in system identification.

Key-Words: - spatial distributed system, system identification, sensor networks, interpolation.

1 Introduction

Wireless Sensor Networks (WSNs) are an important emerging technology that attracted substantial research attention in the last decade [1][2]. WSNs can be seen as a particular type of mobile ad hoc network (MANET) and as one of the main examples of ubiquitous computing. This kind of network is typically a collection of hundreds or thousands of autonomic tiny devices called sensor nodes with limited resources in terms of energy power, computational capacities and radio bandwidth.

Besides the fact the nodes individually possess small computational and energy capacities, the cooperation among them allows the performing of larger task. WSNs are used in various kinds of applications for monitoring and, sometimes, controlling the environment where the network is located. Their wide range of possible applications includes health monitoring, security and military sensing, asset tracking and supply chain management, intelligent agriculture and environmental sensing, home automation and consumer electronics, industrial control and monitoring, etc. Because of their attribute to measure physical quantities (luminous intensity, humidity, barometric pressure, and temperature, as well as sophisticated data such as acoustic, magnetic, global positioning and acceleration signals) in different locations inside the considered process/system, WSN can be involved in system identification procedures for geographically distributed systems [3]-[6].

Physical systems can be categorized into a number of diverse types, dependent on specific characteristics that the system exhibits. Some of these system categorizations are very simple to operate with and have a huge theory base for their analysis. Some system classifications are extremely complex and have still not been examined with any amount of success.

To facilitate the control of a system, first we have to create a model of that particular system. Generally speaking, there are two alternatives for obtaining a model [7]:

1. To use the mathematical theories that govern the domain (physics, chemistry, biology, etc.) in which the specified system is included. In this way, a set of equations is revealed for explaining the dynamics (usually in time domain) of the system to be controlled.
2. To use experimental data, more specifically the measurements of inputs and outputs of the specified system to reveal the model using system identification techniques.

The process of making mathematical models of systems, starting from experimental data, measurements, and observations is called system identification [8][9]. This type of experimentally obtained models is not intended to provide a description of the physical system in totality or in any meaningful way. For controlling a process we should have a mathematical model of its behavior, however understanding the details of that behavior is helpful but needless.

Diverse categories of systems have particular properties that are valuable in their analysis, simulation, prediction, monitoring, diagnosis, and control system design. By correctly identifying a system, we can establish which analysis methods can be used with the system, and ultimately how to investigate and manipulate those systems [10]. In other words, the first step in obtaining an efficient control of a specified process lies in its identification. Classically, a certain model structure is chosen by the researcher, which contains unknown parameters that will be determined by specialized estimation procedures.

This paper presents some methodologies that involve wireless sensor networks in identifying geographically distributed and time variant systems. In this case, WSNs can be considered as a large group of measurement devices that gather data from spatial distributed process in different locations and different moments in time.

2 Preliminaries

System identification is a general idiom to describe mathematical tools and techniques that construct dynamical models from measured data. A dynamical mathematical model in this perspective is a mathematical formalization of the dynamic behavior of a process or system in either the time or frequency domain.

The use of WSN is appropriate for identifying the dynamic behavior of a spatial distributed system [3][6]. In this case, the plethora of sensor nodes gathers measured data from different but relevant in-field positions facilitating the identification process.

In order to develop an identification procedure for geographically distributed systems based on WSN it is appropriate to consider a well-suited sensor network topology relying on the following assumptions:

a) The sensor network is static, i.e., sensor nodes are not mobile; each sensor node knows its own location even if they were deployed via aerial scattering or by physical installation. If not, the nodes can obtain their own location through the location process described in [11]. This assumption is critical in all system identification strategies.

b) The sensor nodes are similar in their computational and communication capabilities and power resources to the current generation sensor nodes.

c) The base station, sometimes called access point, acting as a network controller, as a key server and, in our case, as a main computational resource for identification strategy, is assumed to be a laptop class device and supplied with long-lasting power. We also assume that the base station will not be compromised.

d) Between the three main types of WSN topologies (star, cluster-tree and mesh), we chose the star architecture to be the most suitable for developing identification procedures [12]. In this architecture, a number of base stations are already deployed within 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, as long as they are within the area covered by one cell.

Also, it is possible to extend our methodology to a SENMA (SEnsor Network with Mobile Access) architecture that was proposed in [13] for large-scale sensor networks. The main difference related to the star architecture is that base stations are considered to be mobile, so each cell has varying boundaries which implies that mobile wireless nodes and other appliances can communicate wirelessly, as long as they are at least within the area covered by the range of the mobile access point.

The two types of architectures presented bellow (star and SENMA) have important properties that makes them suitable for low-energy identification methodologies: nodes talk directly to base stations; no node-to-node communications; no multi-hop data transfer; sensor synchronism is not necessary; sensor do not listen, only transmit and only when polled for; complicated protocols avoided; reliability of individual sensors much less critical; system reconfiguration for mobile nodes not necessary.

3. Interpolation Techniques for Spatial Distributed System Identification

Wireless sensor nodes, as a complex and spatially spread sensing system can measure physical quantities relevant for the system under investigation (i.e. the system that has to be identified) and provide data that can be “encapsulated” in a time varying mathematical model.

Due to different deployment strategies (e.g. the sensor nodes could be deployed based on a user-defined raster inside investigating area or could be deployed randomly by aerial scattering) or due to inherent WSN limitations (e.g. energy constraints) we will obtain, at each discrete moment in time, localized measurements, that can be processed to obtain a spatiotemporal mathematical model.

Resolving this kind of problems relies inevitably on interpolation/extrapolation between localized measurement values. In this way the information obtained from a finite number of sensor nodes could be extended using analytical methods upon the entire investigated area. This type of process of spreading localized information in surrounding area is known as space-filling phenomena and creates *surfaces* or *statistical surfaces*.

In 1997, DeMers [14] affirms that any measurable values occurring throughout an area can be considered as a surface and measurements act as *Z*-values i.e. adding the vertical dimension. To estimate the level of that particular physical quantity (measured by sensor nodes) in any user defined point location, we need to know first whether the point of interest is exactly the location point of a sensor node, or in between. In the first situation, the value can be taken directly from the WSN measurement database, in the second case; we need to use an interpolation/extrapolation method to obtain it.

Interpolation is defined as the analytical method of estimating output values within the range of discrete set of known/measured data points. On the other hand, *extrapolation* is defined as the analytical method of estimating output values outside the range of discrete set of known/measured data points.

Using proper interpolation techniques [15], at each moment in time we will obtain a surface representing the identified model of the spatial distributed system. In Fig.4-6 it is presented an example on how spatial distributed system identification can be performed: based on measurements provided by sensor nodes located in the investigated area according to Fig.4, the interpolation surface at that particular moment in time is presented in Fig.6.

To obtain the interpolation surface in the form $z = f(x, y)$ starting from usually nonuniformly distributed measurements represented by the triplet (x, y, z) we use the griddata Matlab function, which encloses linear, cubic or nearest-neigbour interpolation techniques. We have to mention that the surface always passes through the data points.

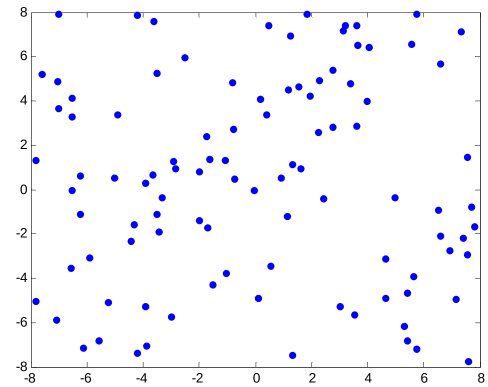

Fig. 4: The deployment of the sensor nodes within the investigated area

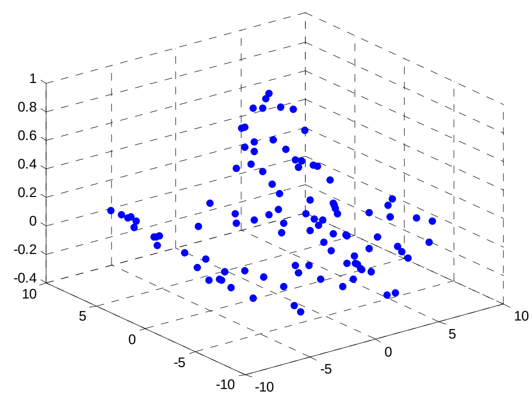

Fig. 5: Measurement data gathered from the sensors deployed inside the investigated area

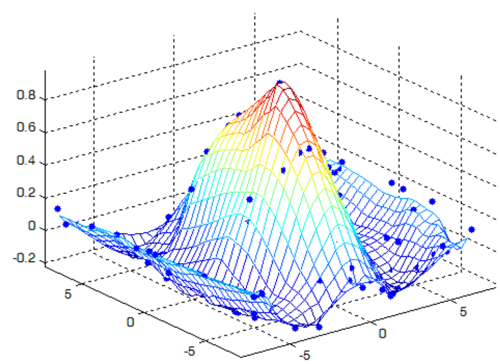

Fig. 6: Interpolation surface and the measurement data of the sensor nodes

Another type of data provided by sensor nodes that can be used in distributed system identification is described using vector fields. An example of such an application is the measurement in different locations of the wind speed and direction. This type of measurement data are represented by vectors within the investigated area (an example is presented in Fig.7) and, using interpolation/extrapolation techniques (based on superposition of two interpolations), an estimated vector field can be obtained (Fig.8).

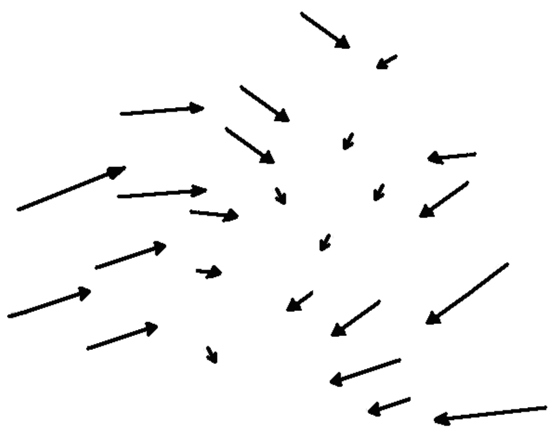

Fig. 7: Vector Measurements within the investigating area

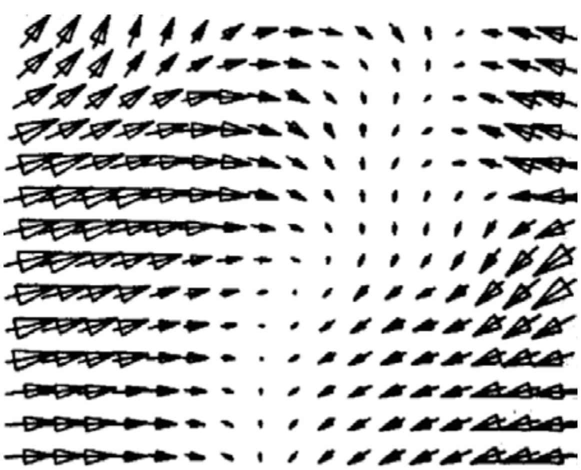

Fig. 8: Vector field obtained by interpolation/extrapolation techniques

4 Conclusion

This paper presented the use of two classical interpolation techniques for system identification in case of spatial distributed processes. The technology provided by wireless sensor networks makes these interpolation approaches suitable and efficient for a large variety of systems.

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