Department of Computer Science
School of Engineering
University of Valencia

Wireless Sensor Networks and Kriging

Julio A. Valle Poblete

Advisors
Dr. Santiago Fellici Castell
Dr. Juanjo Perez Solano

Thesis submitted for the Degree of Master of Science (M.Sc.)

May 2010

... To my lovely and beautiful Laura.
... To my friends Mattia, Luca, Laura, Lissa.
... To my friends from the San Roque rugby team,
... and of course, to all my family:
my parents, brothers, nephews and so on,
thanks for be in my life. Thanks.

Acknowledgements

I would like to acknowledge to all my teachers in the University of Valencia, specially to Santiago Fellici and Juanjo Perez who helped me into the evolution and conclusion of this Master Thesis. Thanks to my classmates too: Hipolito, Amel and Leonidas.

My acknowledgment to my colleagues in Movistar Chile too. I really appreciate their support in my adventure in Valencia. Specially to Luis Machuca, Antonio Bueno and Gustavo Marambio.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

This present work correspond to the final step in order to obtain the degree of *"Master in Advanced Sciences of Modern Telecommunication"* offered by **Universidad de Valencia**, in Valencia city, Spain (20). The main idea behind this report is try to put together the concepts learned through the different subjects that compound Master Program via a specific research methodology.

For me is attractive the large number of potential new applications that require information provided by sensors. For example, applications in medicine and patient care, precision agriculture, environmental monitoring, energy efficiency, households, industrial environments, security, automation, etc. In the other hand, thanks to advances in micro-electro-mechanical systems and wireless communications is possible to build smaller and portable autonomous devices, capable of self-organized, and communicate through the air in order to obtain values of a phenomenon under study in a cooperative way, giving rise to the concept of a wireless network composed by sensor nodes, a Wireless Sensor Network.

Sensor networks differ from traditional networks in many aspects, such as nodes or sensors that have a dual function: are the endpoints of the network and formed the communication network through which the data are transported. Also, the sensor nodes, are limited in life-time, storage and processing capacity. These factors combined with the specific requirements of each application is expressed in limitations or constraints that must be solved through the development of new (or improvement the existing) hardware platform, communication protocols, management tools and applications. Many research groups are working on sensor networks, using techniques of traditional networking as well as also techniques from other scientific areas, e.g. geostatistic techniques, optimization techniques, cross-layer approach, etc.

One of the most famous and useful geostatistic technique is Kriging. The Kriging Technique is a process at which is possible interpolate or estimate the value of a variable under study in terms of discrete values obtained from the same variable at different spatial points within a given region of interest. It is a spatial interpolation method. The discrete variable values are modeled so that it can represent the spatial correlation between them, giving rise to the function Variogram. Then we can form a spatial map representing the variation of the variable in the area without need of take samples at each point in the region.

The Kriging Technique is useful to solve some inherent problems from sensor networks such as: minimizing the number of sensors deployed, build a spatial map of the variable, helps choose the best place to locate the sensors, optimize the use of energy, among other options.

This report present an investigation of the recent literature involving the union of the two concepts described above, i.e. a survey on sensor networks and Kriging Techniques. The research was made in three main sites: ACM, Elsevier and IEEE Explorer considering the main words Kriging and *Wireless Sensor Networks* and the papers found are described under various criteria, such as the problem of sensor network that tries to solve, contribution, methodology, characteristics of the sensor network used, etc. The main objective of this survey is to show the *State of the Art* of the usage of geostatistical Kriging techniques in sensor networks to help those researchers who are facing a similar problem and to the generation of new ideas to help improve the performance and application of sensor networks.

This report is not a detailed study of spatial interpolation techniques applied to sensor networks. The Kriging Technique is not the only one who can carry out this task, but it is one that has received more attention. This report can serve as a milestone for future experimental research on the implementation of the Kriging technique, or research that taking account and compare different interpolation techniques.

The rest of the report is organized as follows: In chapter 2, the sensor networks are presented. Its applications, design considerations, communications protocols and current challenges are described. In Chapter 3 the fundamentals of the Kriging technique are discussed by addressing the concepts of empirical variogram and its models with the two types of Kriging interpolation more common: simple and ordinary Kriging. Also two examples of spatial interpolation process are developed, one shows the way to calculate the weights in a Kriging System and the second example simulate the estimation process with the statistical software *R* and its *geoR package*. Next, the results of the literature survey are shown in Chapter 4 through the description of the selected works. The advantages and disadvantages about Kriging interpolation technique are provided in Chapter 5; some works that deal with Kriging and other interpolation techniques, for example Inverse Distance Weight, are provided too. Finally, the report ends with a final remarks section in Chapter 6.

Chapter 2

WSN Wireless Sensor Network

2.1 Introduction

"A Wireless Sensor Network (WSN) is a collection of spatially distributed smart nodes that use wireless communication for build a network with the aim of monitor, in a cooperative way, an interested parameter within an determined region."

These smart nodes (or autonomous sensors) are low power devices equipped with one or more sensors, a processor, memory, a power supply, a radio, and an actuator (2) (37). Often, the spatial distribution of the nodes is not pre-determined. This allow random deployment in inaccessible or disaster relief zones. Of course that in a controlled environment, the deployment can follow a pre-defined order. The authors in (37) classified WSNs into two types: structured and unstructured. An unstructured WSN is one that contains a dense collection of nodes deployed in an ad hoc or random manner. The network is left unattended to perform monitoring and reporting functions. Managing and detecting failures is difficult since there are so many nodes. In the other hand, in a structured WSN, all or some of the sensor nodes are deployed in a pre-planned manner improving management and maintenance of the network.

Features that must have a WSN are flexibility, fault tolerance, high sensing fidelity, low-cost, rapid deployment and self-organizing capabilities. These characteristics are attractive for develop applications in different research areas such as military, security, natural disaster, biomedical health, hazardous environment exploration and seismic sensing. In words of Yick, Mukherjee and Ghosalin (2): *"we envisioned that, in future, wireless sensor networks will be an integral part of our lives, more so than the present-day personal computer".*

But, this *new* technology presents unique features and requirements that are not take account by neither traditional hierarchical networking nor ad hoc networking techniques. Some of these unique features are:

- A huge number of sensor nodes in a sensor network,
- sensor nodes can be densely deployed,
- sensor nodes are prone to failure,
- sensor wireless network suffer frequently topology changes,
- sensor wireless network use a multihop infrastructureless architecture,
- sensor nodes use mainly broadcast communication,
- sensor nodes are limited in power, computational capacities, and memory,
- sensor nodes don't have global identification, ID.

Due to unique features described above, a set of *constraints* are introduce and should be addressed by protocols and algorithms used in WSNs. Some constraints are: limited energy, short communication range, low bandwidth, limited storage and processing capabilities in each node. Then, is necessary introduce new design concepts, create (or improve the existing) communication protocols, build new applications, and develop new algorithms.

In the remainder of this chapter current applications, factors and key issues to consider in the design of a WSN are described briefly. Next, some existing communication protocols used are displayed. Finally, the challenges and problems which face the WSN are discussed.

2.2 Applications

Today exist different types of sensors, such as seismic, low sampling rate magnetic, thermal, visual, infrared, acoustic, radar. They are able to monitor different ambient conditions: temperature, humidity, vehicular movement, lighting condition, pressure, soil makeup, noise levels, presence or absence of objects, mechanical stress levels, characterization of an object (speed, direction, size). Also, the sensor can be used for continuous sensing, event detection, location sensing, and local control of actuators.

When put together the individual sensor capabilities in a cooperative way around a common task, i.e. in a network, a great number applications are available and new potential application can appear. Some applications are present in diverse areas, e.g., military, environment, health, home, commercial, space exploration, chemical processing and disaster relief.

In recent literature, two main WSN applications categories are exposed: monitoring applications and tracking applications. Monitoring applications include indoor/outdoor environmental monitoring, health and wellness monitoring, power monitoring, inventory location monitoring, factory and process automation, and seismic and structural monitoring. Tracking applications include tracking objects, animals, humans, and vehicles.

The curious reader can find a good list of different application in (2) and (37). Some of them have been deployed and tested in real environment. The main issue about WSN applications is that each application needed specific hardware platforms, software development and new or modified communication protocols. Today, a lot of effort is dedicated to obtain more reliable and robust applications based on information provided by WSN.

2.3 Factors Design and Key Issues

When design an WSN for an specific application dont forget that this kind of network have particular conditions. E.g., each node plays the dual role of data originator and data router (remember the unique features described in section 2.1 too). Then, is necessary considers several factors that influences the WSN design: fault tolerance, scalability, production cost, operating environment, sensor network topology, hardware constraints, transmission media and power consumption. Below some of these factors are discussed (2).

- Fault tolerance: Is the ability to sustain sensor network functionalities without any interruption due to sensor node failures. The fault tolerance level depends on the application of the sensor networks. The physical and logical topology must be developed with this in mind.

- Scalability: Some applications include a huge number of sensors. The WSN must be able to work with this great number, including areas with dense deployment of sensors.

- Production cost: If the cost of the WSN is more expensive than deploying traditional sensors, then the sensor network is not cost-justified.

- Hardware constraints: Associated with the size of the nodes and his energy consumption.

- WSN Topology: Sensor nodes must be capable of self-organized themselves and support device failures. Device failures is a common event due to energy depletion or destruction. Then, the WSN are prone to topology changes after deployment.

- Ambient: The WSN's nodes operate under extreme conditions like high pressure, heat, cold, noisy environment, etc.

- Transmission Media: Radio Frequency (into ISM band), infrared and optical technologies are available for data transmission for sensors communications.

- Power consumption: In WSN power efficiency is an important performance metric, directly influencing the network lifetime, and must be take account by the application's protocols. The power consumption is divided into three domains; sensing, communication, and data processing.

The main constraint in WSNs is the power consumption (or energy conservation) issue. It differ from traditional networks in the limited energy capacity of the nodes (sensors). The common way to supply energy is via a battery that deplete its charge in time. Hence, the design of a WSN must be careful with the power consumption in all levels: hardware, communication protocols and applications. In (37) are discusses the *Energy harvesting* and *Minimizing energy* concepts. Energy harvesting involves nodes replenishing its energy from energy source. Potential energy sources include solar cells, vibration, fuel cells, acoustic noise an a mobile supplier. Minimizing energy (or energy conservation) maximizes network lifetime and is addressed through:

- Efficient and reliable wireless communication,
- intelligent sensor placement (with adequate coverage),
- secure and efficient storage system,
- data aggregation and
- data compression.

2.4 Communication Protocols

The WSN nodes are deployment within an interesting region or field in a random or pre-determined manner without infrastructure. The WSN's node takes samples from the environment and transmit this information to an specific task node, the sink, in charge of collect the data from all sensor. Then, commonly the sink is connected to an infrastructure network where the data are processed. Figure 2.1 (2) exposes this situation.

The communication of sensor nodes is regulated through a set of communication protocols in order to set a standard data representation, signaling, and error detection required to send information over the wireless media. The protocol stack used in WSN is composed by five layers: *Application, Transport, Network, Data Link, and Physical.* Furthermore, exists three different *Management Planes* with the aim of support all layers in terms of task, mobility, and power. The protocol stack and the management planes are exhibited in Figure 2.2 (2).

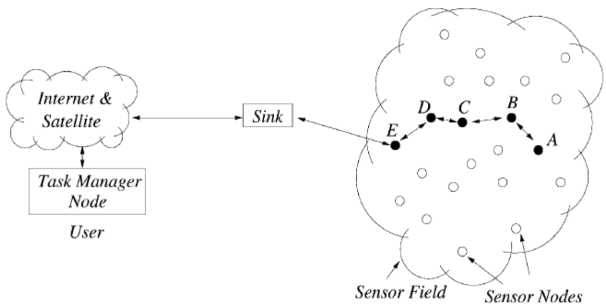

Figure 2.1: Sensors nodes in a region.

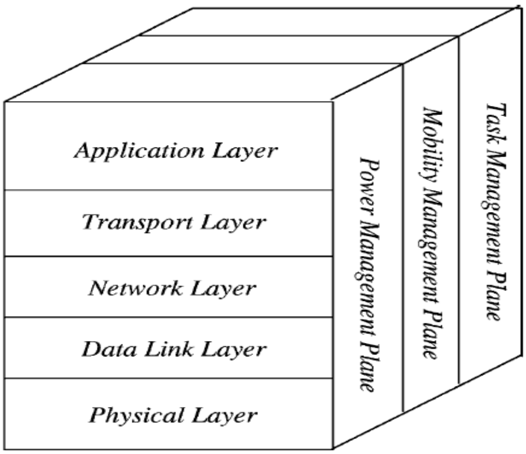

Figure 2.2: WSN Protocol Stack.

The protocol stack combines power and routing awareness, integrates data with networking protocols, communicates power efficiently through wireless medium, and promotes cooperative efforts of sensor nodes. The layers of the protocol stack are described below;

- Application Layer: Different types of application software can be built with application-specific characteristics and requirements. It is the interface between the network and user.
- Transport Layer: Helps to maintain the flow of data if the application requires it.
- Network Layer: Takes care of routing the data supplied by the transport layer.
- Data Link Layer: Management of medium access control, in a power aware way and avoiding (or minimizing) packet data collisions.
- Physical Layer: Deal with simple and robust modulation, transmission and receiving techniques.

The management plane's aim is coordinate the collaboration of the sensor nodes in order to prolong the WSN lifetime. The planes deal with;

- Power Management Plane: How a sensor node uses its power.
- Mobility Management Plane: Detects and registers the movement of sensor nodes.
- Task Management Plane: Balances and Schedules the sensing tasks given to a specific region.

The protocol stack must be energy efficient in term of communications and must be able to work efficiently across all sensor nodes. But the traditional layered approach adds overhead in each layer, becoming inefficient in terms of energy and effectiveness. If the protocol stack is consider like a system more than a individual layers, the information can be shared among layers, minimizing the overhead and taking it to a *cross-layer* approach. Cross-layer designs improve performance and optimize interaction between layers via the sharing of information across layers. Some recent research and open research issues about cross-layer design are described in (37).

2.5 Challenges

The flexibility, fault tolerance, high sensing fidelity, low-cost and rapid deployment characteristics of *new* WSNs technology, are useful for many applications in different research fields. These specific characteristics coupled with features and requirements of each application creates constraints that should be take account in the design and deployment of WSNs. Furthermore, must be able to tackle *new problems* not shown in other networks such as:

- Coverage problem,
- frequent topology changes,
- limited energy resources,
- sensor nodes provide discrete values of the phenomena instead to continuous information in time and/or space,
- application software that be capable of represent the raw data supplied by sensor nodes in a readable way,
- determine the minimum number of sensor nodes for a specific sensing task,
- determine the place where each sensor node will be placed inside a region.

Some of these problems can be addressed by the use of geostatistics techniques. In particular, the Kriging Techniques based over statistical approach of a random process can be helpful in order to estimate the optimal sensor placement locations and/or estimate the value of the interesting parameter (from phenomena under study) in places where it is impossible put a sensor node. Another point of view is use the Kriging technique in the *coverage hole* problem (35) (1) for reach an adequate cover in the desired area using efficiently the energy resources. In the following chapter the fundamentals of Kriging techniques will be show.

Chapter 3

Kriging: A Geostatistical Tool

3.1 Introduction

In the 50's decade the useful mineral reserves evaluation was the fundamental activity that motivated the application of the theory of Random Functions to the reconnaissance and estimation of natural phenomenon. That is the Geostatistic. G. Matheron (22) (24) (23) coined this term from previous work of H. Sichel (31), D. Krige (16), and B. Matern (21). In the last 30 years the Geostatistic has been carried out and consolidated as an applied science that solves practical and concrete problems. Geostatistic study the variables distributed in space from a representative part of the phenomenon under studies. The fundamental element used is the analysis of the spatial distribution of the available information. In this process, the best linear and unbiased estimator is obtained, that is the Kriging, where the variance of the estimation error is minimized. That is nowadays used in mining companies and is every time most used in other fields of the Earth's Science. Lets see formal definition:

From G. Matheron (22) (24) (23), a geological point of view: *"Geostatistics is the application of the formalism of random functions to the reconnaissance and estimation of natural phenomena. Is used in a ge-*

ological context to denote theory and methods for inferring ore reserves from data spatially distributed throughout an ore body."

From N. Cressie (7), with a universal point of view: *"For me, geostatistics has thrown off its earthly shackles and has taken on a more universal role, one that is concerned with statistical theory and applications for processes with continuous spatial index."*

The geostatistic's origins are found in mining. Sichel noted the asymmetrical distribution of mineral content of the gold deposits in South Africa, it was matched to a log-normal distribution and expressed the formulas for this distribution. The weakness of this technique is that it assumes data independence, contradicting the fact that there were richer areas than others. This weakness was remedied by Krige, who proposed a variant of the method of moving averages (*Def. Method of Moving Averages: A statistical method used to analyze a data set mode to create series of points averages. So moving averages are a list of numbers in which each is the average of a subset of the original data*). Finally the rigorous formulation and solution of the problem of estimation was given by Matheron in 1962 [4] who states that geostatistics is the application of theories of regionalized variables (*Def. Regionalized Variables: 1. Variable distributed in space representing a spatial correlation structure. 2. Numerical variables distributed in space. 3. Mathematically, a function that takes a value for each point in space*). Regionalized variables have two complementary aspects: one random, associated with erratic and unpredictable variations of the variable, and a structured, or deterministic, general appearance that reflects the overall characteristics of variation of regionalized phenomenon. Due to the random aspect of the regionalized variable, it is impossible to describe by a continuous function.

The aim of geostatistics is the characterization of a natural phenomenon, leading to various types of applications. Of these, highlights the estimated value of a parameter of interest based on a set of samples. In addition to providing estimates of the parameter, provides a measure of their uncertainty. Therefore, geostatistics can help to select the sampling points so as to minimize the uncertainty of estimation. Many environmental processes exhibit spatial variations on which can be applied geostatistics techniques. These techniques had been used in sciences such as geology, mining, hydrology, meteorology, epidemiology, etc.

As mentioned earlier, geostatistics considers the variables as random functions with two components, deterministic and random, with the aim of represent the variable's spatial dependence [7]. The deterministic section represents non spatial influences and random section is interpreted as the realization of a random field. This random field (spatial stochastic process) can be characterized by statistical moments, i.e. as the covariance function or variogram (or semivariogram). This characterization is useful to interpolate values of the random field in positions where not samples exist, based on the sampled values at nearby positions, i.e. applying Kriging technique. In summary, the variogram describe the spatial correlation and Kriging employs the variogram model in order to generates the best linear unbiased estimate at each location.

This chapter continues with section 3.2 where fundamentals concepts about interpolation are discuss. Next, in section 3.3 the Variogram function is presented with its estimation process and its empirical models. Then, section 3.4 exhibit the Kriging technique and its two more important types, Simple Kriging and Ordinary Kriging. Finally in section 3.5 two examples are shown; In the first example the weights from a Kriging System are calculated. In the other example, a spatial interpolation process is simulated using the statistical software *R* and its *geoR package*. Both examples consider the Ordinary Kriging Technique.

3.2 Background

Let D denote a region of interest, where $D \subset R^d$ (Euclidean space, dimension d). In many real situation, $d = 2$. Each point $s = (x, y) \in D$ can be described by an x and y coordinate in the plane. Within the region D we want to measure some variable z. Let $z(s)$ denote the random variable that can be measured at location s in the region. In practice, measurements are obtained at a finite number n of points. Data then looks like:

$$z(s_1), z(s_2), ..., z(s_n). \tag{3.1}$$

A very simple model for geostatistical data is

$$z(s) = \mu + \epsilon(s). \tag{3.2}$$

The error $\epsilon(s)$ is assumed to have a mean of zero in which case

$$E[z(s)] = \mu. \tag{3.3}$$

Another common assumption is that of *homoskedasticity* or *homoscedasticity* for all points $s \in D$. In statistics, a sequence or a vector of random variables is *homoscedastic* if all random variables in the sequence or vector have the same finite variance, .i.e.

$$var[z(s)] = \sigma^2. \tag{3.4}$$

Now, remember that auto-covariance function for a stationary time series only depends on the lag between the time points; Similarly, for geostatistical data, the covariance functions for the response z at two different points s_1 and s_2 depend only on the difference in locations (distance and direction) between the two points:

$$cov[z(s_1), z(s_2)] = c(s_1 - s_2) \tag{3.5}$$

for some function c. Spatial data that satisfy the conditions of 3.2, 3.3 and 3.4 is called *second-order stationary.* Additionally, if the covariance function depends only on the difference between the two points, then it is called *intrinsically stationary.* Furthermore, if the covariance function depends only on the distance between two points, s_1 and s_2, the spatial process is called *isotropic.* A spatial process is said to be *anisotropic* if the dependence between the response z at two points depends not only on the distance, but also on the direction of that difference. Anisotropic process are commonly due to the underlying process evolving differentially in space.

3.3 Variogram

The function *Variogram* is used for spatial data, its purpose is represent the relationship between the measured values depending on the distance that separates them inside an interesting region. In other words, represents an index of change that shows an variable respect to distance. Consider the sampled value of the variable at two different locations $z(s_1)$ and $z(s_2)$ inside region D. If the variance of the difference $z(s_1) - z(s_2)$ depends only on the difference $s_1 - s_2$, is possible write

$$var[z(s_1) - z(s_2)] = 2\gamma(s_1 - s_2), \tag{3.6}$$

the function 2γ is called **Variogram** and function γ is the **Semivariogram** (22).

Now, suppose constant mean $\mu(s) = 0$ for measured values at each point in region D. Is possible write

$$var[z(s_1) - z(s_2)] = E[(z(s_1) - z(s_2))^2]. \tag{3.7}$$

For definition of variogram,

$$\gamma(s_1 - s_2) = 0.5E[(z(s_1) - z(s_2))^2] \tag{3.8}$$

and

$$\begin{aligned}
0.5E[(z(s_1) - z(s_2))^2] &= 0.5E[(z(s_1) - z(s_2) + \mu - \mu)^2] \\
&= 0.5[E[(z(s_1) - \mu)^2] + E[(z(s_2) - \mu)^2] \\
&\qquad - 2E[(z(s_1) - \mu)(z(s_2) - \mu)]] \\
&= 0.5[Var(z(s_1)) + Var(z(s_2)) - 2Cov(z(s_1), z(s_2))] \\
&= \sigma^2 - Cov(z(s_1), z(s_2)) \\
&= \sigma^2[1 - \rho(z(s_1), z(s_2))],
\end{aligned} \tag{3.9}$$

assuming the variance is also constant through out the region. Here, ρ is the auto-correlation function between two spatial points. Let h denote the distance (or *lag*) between the two points $z(s_1)$ and $z(s_2)$. Hence, the variogram for an isotropic process in terms of auto-correlation function can be written as

$$2\gamma(h) = 2\sigma^2(1 - \rho(h)). \tag{3.10}$$

In terms of auto-covariance function, the variogram function become

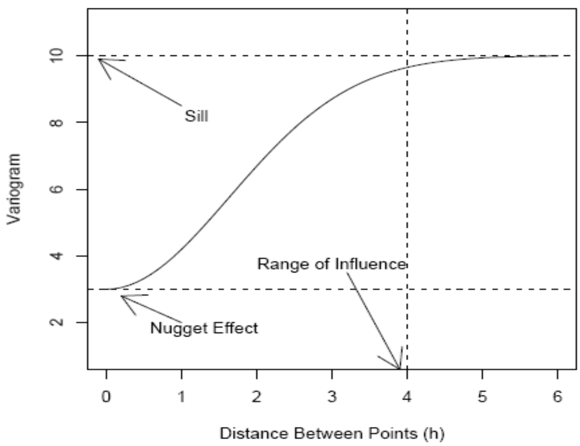

Figure 3.1: A theorical Gaussian Model Variogram.

$$\gamma(h) = \sigma^2 - Cov(h). \tag{3.11}$$

From the previous expression is easy to see that h become larger, the variogram converges to σ^2. Figure 3.1 shows a theoretical variogram. As the distance h gets larger, the variogram values increase indicating that as points get farther apart, the expected difference between the measured values at those two points increases as well.

The variogram can be described based on the follow attributes (see Figure 3.1):

1. The Sill: Correspond to the maximum height of the variogram curve. As h gets large, the correlation (and hence covariance) between the measured values at two points separated by a distance h become independent. In this case, the sill in the variogram plot corresponds to two times the variance.

2. The Range: The range is the distance h such that pairs of sites further than this distance apart are negligibly correlated. The *range of influence* is sometimes defined as the point at which the curve is 95/100 of the difference between the nugget and the sill.

3. The Nugget Effect: Is logical expect that $2\gamma(0) = 0$, i.e. $Var[z(s_1) - z(s_2)]$ should equal zero if $s_1 = s_2$. However, this is usually not

the case. As the distance h goes to zero, there tends to be a *nugget effect* due to measurement error and micro-scale variation.

In practice, the variogram is estimated based on the measured values take in different locations inside region D, Then, the called *empirical variogram* is obtained. But, in order to be useful, this empirical variogram need be replaced by a model. The next two sub-sections deal with the variogram estimation and its mathematical models.

3.3.1 Estimation of the Variogram

The *classical* method of estimating the variogram, which corresponds to the method of moments estimator, is given by (22):

$$2\hat{\gamma}(h) = \frac{1}{|N(h)|} \sum_{N(h)} [z(s_i) - z(s_j)]^2, \tag{3.12}$$

where $N(h)$ is the set of all distinct pairs of points $z(s_i)$; $z(s_j)$ such that $\|s_i - s_j\| = h$. In practice, the data is smoothed to generate an estimate of the variogram. For instance, the data can be partitioned into groups where observations in particular groups are within a certain range of distance apart and then using the average squared difference of the points in each group to replace the sum in 3.12.

The method of moments is not strong for extremes values $z(s_i)$. Furthermore, some authors consider the data distribution is biased. Cressie and Hawkins in 1980 (25) proposes an unbiased estimator for $2\gamma(h)$. For further details see (7).

3.3.2 Variogram Models

The Kriging technique will need access to variogram values for distances other than those used in the empirical variogram. Furthermore, the variogram used in Kriging process need to obey certain numerical properties (needs to be *non-negative definite*) in order to be trusted. Therefore, is necessary to adjust the empirical variogram in a model. Some of the most common models are presents below, where S is the sill, a is the influence range and $\gamma(0) = c$ the nugget effect.

1. Spherical Model:

$$\gamma(h) = \begin{cases} c + (S-c)[1.5(\frac{h}{a}) - 0.5(\frac{h}{a})^3], \text{ for } h \leq a \\ c, \text{ otherwise.} \end{cases} \tag{3.13}$$

2. Exponential Model:

$$\gamma(h) = c + (S-c)[1-(e)^{\frac{-3h}{a}}]. \tag{3.14}$$

3. Gaussian Model:

$$\gamma(h) = c + (S-c)[1-(e)^{\frac{-3h^2}{a^2}}]. \tag{3.15}$$

4. Power Model:

$$\gamma(h) = c + Ah^w. \tag{3.16}$$

In some cases, the empirical variogram can be modeled by a linear combinations of models.

3.4 Kriging

"In geostatistics, correspond to process of predict the ore grade in a mining block from observed samples." (22)

"Minimum-mean-squared-error method of spatial prediction that (usually) depends on the second-order properties of the process $Z(\cdot)$" (23) (7)

Consider a linear (or rather affine) estimate $\hat{z}_0 = \hat{z}(s_0)$ at location s_0 based on N measurements $z = [z(s_1), ..., z(s_n)]^T = [z_1, ..., z_n]^T$,

$$\hat{z}_0 = w_0 + \sum_1^N w_i z_i = w_0 + w^T z, \tag{3.17}$$

where w_i are the weights applied to z_i and w_0 is a constant.

Consider z_i as realizations of stochastic variables Z_i, where $\bar{Z} = [Z(s_1), ..., Z(s_n)]^T = [Z_1, ..., Z_n]^T$. Furthermore, consider $Z(s)$ as consisting of a mean value and a residual $Z(s) = \mu(s) + \epsilon(s)$. Suppose the residual with mean value zero and constant variance σ^2, i.e. $E[\epsilon] = 0$ and $Var[\epsilon] = \sigma^2$. For the linear estimator is possible write

$$\hat{Z}_0 = w_0 + \bar{w}^T \bar{Z}. \tag{3.18}$$

The estimation error $z_0 - \hat{z}_0$ is unknown. But using the expectation value of the estimation error, the following relation is established

$$E[Z_0 - \hat{Z}_0] = E[Z_0 - w_0 - \bar{w}^T \bar{Z}] = \mu_0 - w_0 - \bar{w}^T \bar{\mu}, \tag{3.19}$$

where $\mu_0 = \mu(s_0)$ is the expectation value of Z_0 and $\bar{\mu}$ is a vector of expectation values for $\bar{Z}$

$$\bar{\mu} = \begin{bmatrix} \mu(s_1) \\ \vdots \\ \mu(s_n) \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_n \end{bmatrix}. \tag{3.20}$$

The estimator should be unbiased or central, i.e., $E[Z_0 - \hat{Z}_0] = 0$ or

$$\mu_0 - w_0 - \bar{w}^T \bar{\mu} = 0. \tag{3.21}$$

The variance of the estimator error is

$$\begin{aligned} \sigma_E^2 &= Var[Z_0 - \hat{Z}_0] \\ &= Var[Z_0] + Var[w_0 + \bar{w}^T \bar{Z}] - 2Cov[Z_0, w_0 + \bar{w}^T \bar{Z}] \\ &= \sigma^2 + \bar{w}^T (Cw - 2Cov[Z_0, \bar{Z}]), \end{aligned} \tag{3.22}$$

where C is the dispersion of variance-covariance matrix of the stochastic variables Z entering into the estimation, derived from the input variogram model. The idea behind Kriging is *find the linear estimator which minimizes the estimation variance.*

3.4.1 Simple Kriging

In simple Kriging SK is assume that $\mu(s)$ is known. From equations 3.18 and 3.21

$$\hat{Z}_0 - \mu_0 = \bar{w}^T(\bar{Z} - \bar{\mu}). \tag{3.23}$$

The weights w_i are found by minimizing the estimation variance σ_E^2. This is done by setting the partial derivate to zero

$$\frac{\partial \sigma_E^2}{\partial w} = 2Cw - 2Cov[Z_0, \bar{Z}] = 0, \tag{3.24}$$

which results in the SK system

$$Cw = Cov[Z_0, \bar{Z}] \tag{3.25}$$

or

$$\begin{bmatrix} C_{11} & \cdots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{n1} & \cdots & C_{nn} \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} C_{01} \\ \vdots \\ C_{0n} \end{bmatrix}, \tag{3.26}$$

where $C_{ij}, i, j = 1, ..., n$ is the covariance between points i and j among the n points, which enter into the estimation of point 0. $C_{0j}, j = 1, ..., n$ is the covariance between point j and point 0, the point to which interpolate. These covariance are obtained from the variogram model.

The minimized squared estimation error, termed the simple Kriging variance, is

$$\begin{aligned} \sigma_{SK}^2 &= \sigma^2 + \bar{w}^T(Cw - 2Cov[Z_0, \bar{Z}]) \\ &= \sigma^2 - \bar{w}^T Cov[Z_0, \bar{Z}]. \end{aligned} \tag{3.27}$$

In SK the mean value $\mu(s)$ is known. In practice it is often assumed constant for the entire domain (or study area). Another approach is estimate the value of $\mu(s)$ or construct an interpolation algorithm which does not require knowledge of the mean field.

3.4.2 Ordinary Kriging

In ordinary Kriging OK the mean $\mu(s)$ is constant and equal to μ_0 for Z_0 and the n points that enter into the estimation of Z_0. From equations 3.19 and 3.21

$$E[Z_0 - \hat{Z}_0] = \mu_0(1 - \bar{w}^T\bar{1}) - w_0 = 0 \tag{3.28}$$

for any μ_0. $\bar{1}$ is a vector of ones. This is possible only if $w_0 = 0$ and $\bar{w}^T\bar{1} = 1$.

The weights w_i are found by minimizing σ_E^2 under the constraint $\bar{w}^T\bar{1} = 1$. A standard technique for minimization under a constraint is introducing a function F with a so-called *Lagrange Multiplier* (here -2λ) which is multiply buy the constraint, set to zero and then minimizing

$$F = \sigma_E^2 + 2\lambda(\bar{w}^T\bar{1} - 1) \tag{3.29}$$

without constraints. Again the partial derivatives are set to zero

$$\begin{aligned} \frac{\partial F}{\partial w} &= 2Cw - 2Cov[Z_0, \bar{Z}] + 2\lambda\bar{1} = 0 \\ \frac{\partial F}{\partial \lambda} &= 2(\bar{w}^T\bar{1} - 1) = 0, \end{aligned} \tag{3.30}$$

which results in the OK system

$$\begin{aligned} Cw + \lambda\bar{1} &= Cov[Z_0, \bar{Z}] \\ \bar{1}^T\bar{w} &= 1 \end{aligned} \tag{3.31}$$

or

$$\begin{bmatrix} C_{11} & \cdots & C_{1n} & 1 \\ \vdots & \ddots & \vdots & \\ C_{n1} & \cdots & C_{nn} & 1 \\ 1 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_n \\ \lambda \end{bmatrix} = \begin{bmatrix} C_{01} \\ \vdots \\ C_{0n} \\ 1 \end{bmatrix}. \tag{3.32}$$

The values requested for C_{ij} are found as described in the previous section on SK.

The minimized squared estimation error, termed the ordinary Kriging, variance is

$$\begin{aligned} \sigma^2_{OK} &= \sigma^2 + \bar{w}^T(Cw - 2Cov[Z_0, \bar{Z}]) \\ &= \sigma^2 - \bar{w}^T Cov[Z_0, \bar{Z}] - \lambda. \end{aligned} \tag{3.33}$$

OK implies an implicit re-estimation of μ_0 for each new constellation of points. This is an attractive property making OK well suited for interpolation in situations where the mean is not constant (i.e., in the absence of first order stationary).

3.5 Examples

3.5.1 Weights on Ordinary Kriging System

In this example the *weights* from an OK system will be calculated. Consider the 1-dimensional system from Figure 3.2. The sampled values at these locations are: $z_1 = 1, z_2 = 3, z_3 = 2$.

In the other hand, consider that the empirical variogram is modeled with a spherical model variogram 3.13 with parameters $S = 1, a = 6, c = 0$. Finally, remember that the equation 3.11 bring an expression for the auto-covariance function

$$Cov(h) = \sigma^2 - \gamma(h), \tag{3.34}$$

where $\sigma^2 = S = 1$.

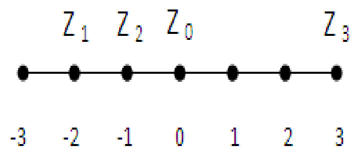

Figure 3.2: Locations in 1 dimension.

Therefore, with the previous considerations is possible to calculate the values of the variogram and auto-covariance functions at different distances. These values are shown in Table 3.1.

h	$\gamma(h)$	$Cov(h)$
0	0.0000	1.0000
1	0.2477	0.7523
2	0.4815	0.5185
3	0.6875	0.3125
4	0.8519	0.1481
5	0.9606	0.0394
6	1.0000	0.0000

Table 3.1: Variogram and Auto-Covariance functions.

Then, the OK system become

$$\begin{bmatrix} 1.0000 & 0.7523 & 0.0394 & 1 \\ 0.7523 & 1.0000 & 0.1481 & 1 \\ 0.0394 & 0.1481 & 1.000 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \lambda \end{bmatrix} = \begin{bmatrix} 0.5185 \\ 0.7523 \\ 0.3125 \\ 1 \end{bmatrix}. \tag{3.35}$$

The solution of the OK System is $w_1 = -0.0407, w_2 = 0.7955, w_3 = 0.2452, \lambda = -0.0489$ and $\sigma^2_{OK} = 0.3949$.

3.5.2 Ordinary Kriging using *R* and *geoR*

In this section a simple example is developed to help further understand the Kriging technique. Through the statistical software *R* (28) and the specific *R package* for geostatistical analysis *geoR* (29) the example is illustrated. *R* is a language and environment for statistical computing and graphics that provides a wide variety of statistical and graphical techniques, and is highly extensible. *R* is available as Free Software under the terms of the Free Software Foundation's GNU General Public License in source code form. Think about *R* like an environment within which statistical techniques are implemented. *R* can be extended via additional specific purpose modules, i.e. *packages*.

The dataset to consider for this example is a dataset included in the *geoR package*, named *s100*. This set contain simulated information about 100 samples, its location and the value of the interest parameter. Below is possible observe a summary of the dataset. Furthermore, Appendix A.1 contains the dataset's detail and the command `points(s100)` displayed a plot with the samples locations, see Figure 3.3.

```
Number of data points: 100

Coordinates summary
        Coord.X    Coord.Y
min 0.005638006 0.01091027
max 0.983920544 0.99124979

Distance summary
        min         max
0.007640962 1.278175109

Data summary
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-1.1680  0.2730  1.1050  0.9307  1.6100  2.8680

Other elements in the geodata object
```

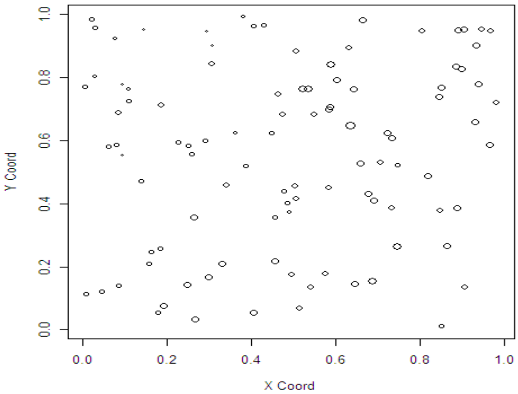

Figure 3.3: Samples Locations of example dataset.

```
[1] "cov.model" "nugget"    "cov.pars"  "kappa"     "lambda"
```

At the moments at which the samples and his values are available, the function Variogram can be built and plotted via the function `variog`. This function allow choose between the *classical* method of moments or *modulus* method suggested by Cressie and Hawkins (25). For this example is considered classical estimator and the command execute correspond to:

```
Vs100 <- variog(s100,option="bin",estimator.type="classical",
uvec=seq(0,1,l=11)),
```

where:

- `s100`: the empirical data set,
- `estimator.type="classical"`: variogram function based on the method of moments,
- `uvec=seq(0,1,l=11)`: lags provided (represented in the distance vector).

The resulting Variogram, Figure 3.4, can be displayed with command `plot(Vs100)` and the details about the empirical Variogram function are show calling the function `Vs100` in the *R* environment, see Appendix A.2, where:

- `u`: distance vector,
- `v`: estimated value at distance u,
- `n`: number of pairs in each bin,
- `sd`: standard deviation of the value in each bin,
- `bins.lim`: limits defining the interval spanned by each bin,
- `ind.bin`: indicate if the number of pairs in each bin is greater or equal to the value in the argument `pairs.min`,
- `var.mark`: variance of the data,
- `beta.ols`: mean part of the model fitted by ordinary least square,
- `output.type`: echoes of the option argument,
- `max.dist`: maximum distance between pairs allowed in the variogram calculations,
- `estimator.type`: echoes the type of estimator used,
- `n.data`: number of data,
- `lambda`: value of the transformation parameter,
- `trend`: trend specification,
- `direction`: direction for which the variogram was computed,
- `uvec`: lag provided in the function call,
- `call`: the function call.

Such as was mentioned earlier in Section 3.3, the empirical variogram must be fitted to a model. The *geoR* package include the possibilities of estimate the parameters of the variogram model "by eye"(function `lines.variomodel`), by least squares fit (function `variofit`), by likelihood based methods (function `likfit`) and bayesian methods (function

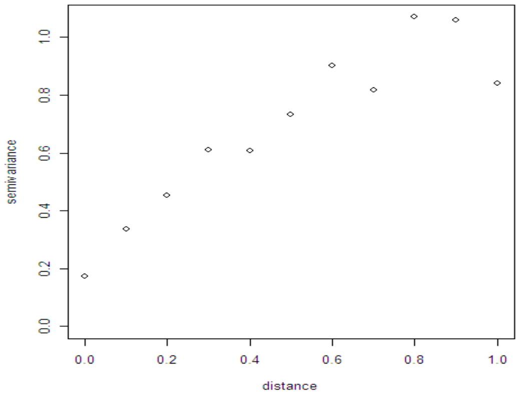

Figure 3.4: Variogram of the example dataset.

`krige.bayes`). For this example a maximum likelihood method is used executing the command:

```
mls100 <- likfit(s100,ini=c(1,0.5),fix.nugget=T),
```

where:

- `s100`: the empirical data set,
- `ini=c(1,0.5)`: initial values for the covariance parameters,
- `fix.nugget=T`: indicate that the nugget variance must regarded as fixed.

Although is not indicate the model of the correlation function that is use in `likfit` command, an exponential model is applied by default. To use different models, exist the argument `cov.model`, where the available options are: `matern`, `exponential`, `gaussia`, `spherical`, `circular`, `cubic`, `wave`, `power`, `powered.exponential`, `cauchy`, `gencauchy`, `gneiting`, `gneiting.matern`, `pure.nugget`.

Use command `lines(mls100)` for see the graphic of model variogram just after of execute the command `plot(Vs100)` in order to put in the same figure the empirical variogram and the modeled variogram. Figure 3.5 represent this situation. A summary of the parameter estimation

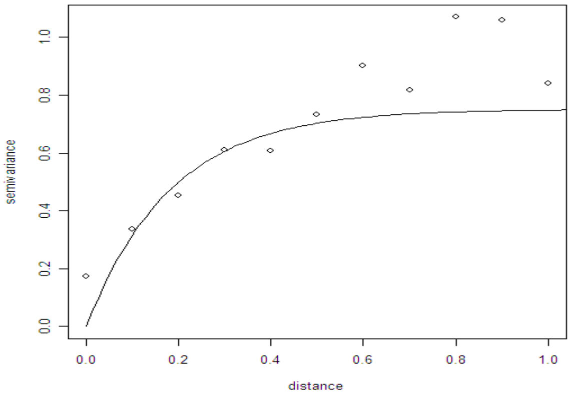

Figure 3.5: Empirical and model variogram of example dataset.

for model variogram is obtained with function `summary(mls100)`, see Appendix A.3.

Now, the spatial interpolation process can be performed. For this, the parameter's values will be estimate in the four points indicated by the *fourpoints* matrix. The function `krige.conv` is in charge of make the estimation using by default *Ordinary Kriging* method, but other method can be used such as *Simple Kriging, Trend (universal) Kriging and External Trend Kriging.* In this example Ordinary Kriging estimation is performed via the command `kfours100` who calls to the `krige.conv` function considering the original dataset, the location of points of interest and the variogram model parameters. The output of the executed command `okfours100` shows the estimate value and its krige variance in the interesting locations. Below is illustrated step by step the implementation of the estimation process.

1. Four point's location.

```
> fourpoints <- matrix(c(0.2,0.6,0.2,1.1,0.2,0.3,1,1.1),
                ncol=2)
>
>
>
```

```
> fourpoints
     [,1] [,2]
[1,]  0.2  0.2
[2,]  0.6  0.3
[3,]  0.2  1.0
[4,]  1.1  1.1
>
```

2. Calling to `krige.conv` function.

```
> okfours100 <- krige.conv(s100, locations = fourpoints,
                krige = krige.control(obj.m = mls100))
krige.conv: model with constant mean
krige.conv: Kriging performed using global neighborhood
>
```

3. Displaying the estimated values.

```
> okfours100
$predict
[1]  0.8977980  1.2452301 -0.7125958  0.7732152

$krige.var
[1] 0.1979621 0.3849767 0.3509200 0.6996152
>
```

Chapter 4

Literature Review

In this chapter will be described the works that involve the WSN and spatial interpolation via the Kriging technique. The literature research was made taking account the WSN technology and the application of some spatial interpolation process based on Kriging technique. The research was made considering the main words *Kriging* and *Wireless Sensor Networks*. Moreover, the works was classify based on the following parameters:

- Keywords: In order to emphasize the main technologies used in the work.
- Field: In order to emphasize the areas where the works can be apply (or were applied).
- Cited by: Show the number of citations in other works according to Google Scholar.
- Contribution: The main and/or novel contribution that expose the work.
- Methodology: In order to emphasize the steps taken for develop the work.
- WSN Contribution: In order to emphasize how the WSN is involve in the work.

- WSN Data: In order to emphasize how the data provided by WSN is use in the work.
- Kriging Contribution: In order to emphasize the propose of the use of the spatial interpolation technique.
- Kriging Type: In order to emphasize the Kriging type technique.
- Variogram: In order to emphasize some comments about the estimation or setting-up of the variogram.
- Comments: In order to emphasize other important issues.

Then the works and its description are displayed.

4.1 Sharing and Exploring Sensor Streams over Geocentric Interfaces (18)

Authors	Luo, Liqian and Kansal, Aman and Nath, Suman and Zhao, Feng.
Source	In Proceedings; GIS '08: Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems.
Publisher	ACM.
Year	2008.
Keywords	Sensor networks, peer produced, geocentric interface.
Field	Systems Infrastructure, Sensor Data Stream Heterogeneous Sensor Networks, Sharing Approach.
Cited by	4, in Google Scholar.

Contribution	Presents to SenseWeb, an open and scalable infrastructure for sharing and spatial-temporal exploration of sensor data stream. Its data exploration front-end, SensorMap, presents sensor streams visually on a map-based interface (interactive geocentric data exploration).
Methodology	The proposed infrastructure it is evaluated on a deployed prototype.
WSN Contribution	One of the diverse sensor network that help to collect data.
WSN Data	Temperature, traffic, and camera sensors in Seattle, weather stations in Le Genepi (Switzerland), weather towers in Wannengrat (Switzerland), camera and rain sensors in Taiwan, and weather stations in Singapore.
Kriging Contribution	Spatial Interpolation algorithm implemented in the data transformers, in order to build a map of the interesting parameter.
Kriging Type	Ordinary.
Variogram	Undescribed.
Comments	Kriging and Inverse Distance Weight are implemented in data transformers for spatial interpolation. Both are compared via performance evaluation. Tradeoff between precision and latency.

4.2 Kriging for Localized Spatial Interpolation in Sensor Networks (35)

Authors	Umer, Muhammad and Kulik, Lars and Tanin, Egemen.

Source	In proceedings; SSDBM '08: Proceedings of the 20th international conference on Scientific and Statistical Database Management.
Publisher	Springer-Verlag.
Year	2008.
Keywords	Systems Infrastructure, Sensor Data Stream Heterogeneous Sensor Networks, Sharing Approach.
Field	Wireless Sensor Network, Distributed, Interpolation Algorithm, Energy Efficiency, Coverage Hole.
Cited by	2, in Google Scholar.
Contribution	Perform accurate spatial interpolation for coverage holes with minimal power requirements. For this, build a correlation model (via Quad Suppress Algorithm QS) for perform interpolation (via Distributed Kriging Algorithm DISK).
Methodology	Design a new technique. Test the performance via simulation. Compare the proposed technique versus global interpolation.
WSN Contribution	Presents an alternative to solve WSN's coverage holes problem.
WSN Data	Two datasets; a Digital Elevation Model (DEM) dataset from the state of Colorado US (8), and simulated traffic data for the city of Melbourne, Australia.
Kriging Contribution	Spatial Interpolation. Alternative to sensor deployment for tackle the problem of coverage holes.
Kriging Type	Ordinary and Distributed Kriging algorithm.

Variogram	Undescribed.
Comments	Variogram variation (QS) and Kriging variation (DISK) are implemented in a distributed approach. Thus, the communication costs are reduced. Hence, is more energy efficient that global interpolations.

4.3 QoM and Lifetime-constrained Random Deployment of Sensor Networks for Minimum Energy Consumption (19)

Authors	Maleki, Morteza and Pedram, Massoud.
Source	In proceedings; IPSN '05: Proceedings of the 4th international symposium on Information processing in sensor networks.
Publisher	IEEE Press.
Year	2005.
Keywords	Energy-awareness, Sensor networks, Mathematical programming/optimization, Random deployment.
Field	Wireless Sensor Network, Optimization Problem, Energy Efficiency, Minimum number of sensor, Routing Algorithm.
Cited by	19, in Google Scholar.
Contribution	State as an Optimization Problem the energy efficient random deployment of sensor network.

Methodology	A node density is set which satisfies the *Quality of Monitoring* QoM constraint. Then, presents a continuous space model for random deployment with the associated routing scheme; Finally give a Spatial distribution of sensor with minimum total energy. All this process is tested via simulation.
WSN Contribution	The paper consider the problem of energy efficient random deployment of WSN.
WSN Data	The energy used by sensors to transmit the data is used for establish the continuous space model (objective function).
Kriging Contribution	Help to define the metric QoM (Quality of Monitoring) that is used for establish one of the constraint of the optimization problem.
Kriging Type	Ordinary.
Variogram	Undescribed.
Comments	In order to state the *Quality and Lifetime-constrained Sensor Deployment Problem*QLSD key assumptions are set: deployment region is circular, sensors nodes generate traffic at a constant data rate, no energy loss due to the MAC layer collision, the sensor nodes are time-synchronized, sensor can find their location after they are deployed, lossless wireless communication between sensors.

4.4 Asymptotic optimality of multicenter Voronoi configurations for random field estimation (9)

Authors	Graham, R. and Cortes, J.

Source	Article; Automatic Control, IEEE Transactions on.
Publisher	IEEE Control Systems Society.
Year	2007.
Keywords	Optimal Estimation, Kriging Interpolation, Optimal Field Interpolation, Prediction Error.
Field	Wireless Sensor Network, Optimization Problem, Field Interpolation.
Cited by	9, in Google Scholar.
Contribution	Characterize the mean-squared error of the simple Kriging estimator as a function of the network configuration. Next, define two optimal criterion: the maximum predictor error and generalized variance of the Kriging predictor.
Methodology	State an Optimization Problem in order to Characterize the optimal configuration for spatial prediction via propositions, proofs, theorems and corollaries. A simulation is performed too.
WSN Contribution	WSN, optimal sensor locations that give rise optimal field interpolation.
WSN Data	Simulations with 5 agents inside a convex polygon.
Kriging Contribution	Characterize the continuity properties of the mean-squared error of the simple Kriging estimator as a function of the network configuration.
Kriging Type	Simple.
Variogram	Undescribed.

Comments	Focus on optimal network configuration for the estimation of the random field at a single snapshot. In other words, select locations to take measurements in a such way as minimize the uncertainty in the estimate of the spatial process.

4.5 Energy-Efficient Map Interpolation for Sensor Fields Using Kriging (11)

Authors	Harrington, Brian and Huang, Yan and Yang, Jue and Li, Xinrong.
Source	Article; IEEE Transactions on Mobile Computing.
Publisher	IEEE Educational Activities Department.
Year	2009
Keywords	Spatial autocorrelation, geosensor networks, sensor networks, energy efficient.
Field	Wireless Sensor Network, Spatial/Temporal Interpolation, Energy Efficiency, Sensor Network Database.
Cited by	1, in Google Scholar.
Contribution	Spatial-Autocorrelation aware, energy-efficient and error bounded framework. Novel Iterative reporting framework, resilient to sensor failures and capable of integration with temporal models.
Methodology	Propose the framework with Kriging as the spatial interpolation method and compare with other interpolation schemes. Experimental evaluation (simulation and real sensor network) of framework; its compared with other techniques.

WSN Contribution	One type of sensor network for apply the proposed framework. Furthermore, the experimental evaluation was done on a Micaz mote sensor network.
WSN Data	For evaluation via simulation: Data from Intel lab data set (54 sensors) and from Global Historical Climatology Network (Asia portion). For evaluation via real network: 25 MICAz motes in 5x5 grid with a length of 4 ft. from one mote to another.
Kriging Contribution	Is the technique used for build the interpolation map of the phenomena. Is performed in the sink.
Kriging Type	Ordinary.
Variogram	Estimated at the sink and propagated to the sensors.
Comments	Three main conflicted goals: minimum number of reporting sensor, minimum coordination costs among sensor, interpolation at sink within an error threshold.

4.6 From wireless sensors to field mapping: Anatomy of an application for precision agriculture (5)

Authors	Alberto Camilli and Carlos E. Cugnasca and Antonio M. Saraiva and Andr R. Hirakawa and Pedro L.P. Corra.
Source	Article; Computers and Electronics in Agriculture.
Publisher	Elsevier.
Year	2007.

Keywords	Wireless sensor networks; Precision agriculture; Indicator Kriging.
Field	Precision Agriculture, Wireless Sensor Network, Simulated Application.
Cited by	15, in Google Scholar.
Contribution	Presents a proof of concepts on how networked sensors can be utilized to construct an on-the-go field data estimate for use in presicion agriculture.
Methodology	An hypotheses is set. Then, the application is simulated in “network simulator ns-2”. The precision and computational complexity are evaluated considering different configurations and interpolations methods.
WSN Contribution	Is an alternative way to collect field data periodically without the use of vehicle to get sampling point. The data reported by WSN is useful for build estimate field.
WSN Data	WSN is simulated. The dataset used in simulation come from literature. Sensor devices were deployed in a 25m grid and the referential data set used as the sensor values at grid positions.
Kriging Contribution	Used for spatial interpolation based on indicator values reported by the sensors.
Kriging Type	Ordinary / Indicator.
Variogram	Undescribed.

Comments	Three different configurations. First, all nodes answer the query from the sink and send their nominal values. Second, all nodes answer the query from the sink and send their *indicator* values. At the end, sensor's indicators data that are inside a predefined region around the location to be estimated are sent to the sink.

4.7 Location-aware system for olive fruit fly spray control (27)

Authors	Costas M. Pontikakos and Theodore A. Tsiligiridis and Maria E. Drougka.
Source	Article, Computers and Electronics in Agriculture.
Publisher	Elsevier.
Year	2009.
Keywords	Location-aware system, Expert system, Geographical Information System, Precision Farming, Olive fruit fly.
Field	Precision Agriculture, Wireless Sensor Network, Location-Aware System.
Cited by	0, in Google Scholar.
Contribution	This article proposes a Location-Aware (LA) system suitable for the ground control of the olive fruit fly combining sensor technologies, wireless Internet, geographical information systems (GIS) and expert systems (ES).
Methodology	A system is built in a layered or modular way. The system architecture is based on 4 modules: Communication module, LA module, GIS module and ES module. Finally, the system is test on a small-scale experiment.

WSN Contribution	The WSN is useful for handling heterogeneous environmental data in a single interface (26).
WSN Data	WSN architecture to transmit the data from an array of sensors to the server over a wireless link is the architecture provided in Pontikakos and Tsiligiridis (26).
Kriging Contribution	Estimate the infestation risk, over experimental area, based on data provided by the heterogeneous sensor network.
Kriging Type	Undescribed.
Variogram	Undescribed.
Comments	The data used for estimate of the infestation risk come from heterogeneous sensor which can be managed in a simple user interface. The idea is hide the complexity of the sensor network and the communication architecture aspects to the user.

4.8 The Minimum Number of Sensors Interpolation of Spatial Temperature Profiles in Chilled Transports (14)

Authors	Jedermann, Reiner and Lang, Walter.
Source	In proceedings, EWSN '09: Proceedings of the 6th European Conference on Wireless Sensor Networks.
Publisher	Springer-Verlag.
Year	2009.
Keywords	Wireless sensor networks, Food logistics, Kriging, Information, Processing, Temperature mapping.

Field	Wireless Sensor Network, Spatial Temperature Profile (Map), Sensor Positioning Strategies, Minimum number of sensor, Cool chains, Chilled Transport.
Cited by	0, in Google Scholar.
Contribution	Method to estimate the minimum number of sensors and to compare different sensor positioning strategies.
Methodology	Experiment on a set of data provided by a WSN. Compare different interpolation methods and evaluate strategies for locations of sensors. Use the interpolation error as an indicator of the probability of sensor fault.
WSN Contribution	Technology used in order to get the samples of temperature in chilled transport. Collect the experimental data for this study from a delivery truck.
WSN Data	Data set split in two groups: one group is used like input in the interpolation model and other group is used like references points. TelosB motes were used for data acquisition. The preliminary tests was performed with data loggers.
Kriging Contribution	Used for build interpolation map. Furthermore, the average prediction error of the ordinary kriging is plotted as a function of the number of source (sensor) point, i.e, can help to choose the minimum number of sensors in order to obtain an acceptable error in the estimation process.
Kriging Type	Ordinary Kriging and Kriging with linear trend.
Variogram	Use Gaussian Model.
Comments	The interpolation process was simulated in Matlab.

4.9 A method for spatial prediction of daily soil water status for precise irrigation scheduling (13)

Authors	C.B. Hedley and I.J. Yule.
Source	Article, Agricultural Water Management.
Publisher	Elsevier.
Year	2009.
Keywords	EM mapping, Soil moisture sensor network, Irrigation scheduling, Soil water status.
Field	Irrigation System, Water Efficiency, Soil Moisture Sensor Network, Soil water status.
Cited by	0, in Google Scholar.
Contribution	A method for predicting daily soil water status is proposed. This prediction is used for improved the irrigation system via an software-controlled automated irrigation system. Then, is possible to reach a water efficiency usage.
Methodology	Experimental. The proposed method is applied over maize field.
WSN Contribution	In this work is not used a WSN network to get the input data from the field, but is mentioned like an alternative to get the samples data.
WSN Data	The best option to get the samples data.
Kriging Contribution	Used to produce a soil EC(Electrical Conductivity) prediction surface map.

Kriging Type	Ordinary.
Variogram	Spherical model.
Comments	In order to get a more accurate interpolation of the soil water is need get a greater number of samples. In this scenario, the use of a WSN for get the samples is the best option as such as is shows in the irrigation system proposed in (15).

4.10 Remote Sensing and Control of an Irrigation System Using a Distributed Wireless Sensor Network (15)

Authors	Yunseop Kim and Evans, R.G. and Iversen, W.M.
Source	Article, Instrumentation and Measurement, IEEE Transactions on.
Publisher	IEEE Instrumentation and Measurement Society.
Year	2008.
Keywords	Automation, control systems, measurement, portable radio communication, sensors, water resources.
Field	Irrigation System, Water Efficiency, Automation, Control System, Wireless Sensor Network.
Cited by	12, in Google Scholar.

Contribution	In traditional irrigation systems the water is applied in a uniformly way across the field. In this works is proposed an alternative to traditional irrigation system using in-field WSN in order to take samples of soil properties and water availability with the aim to decide if is proper the irrigation or not.
Methodology	Experimental. The proposed system is applied on a small field.
WSN Contribution	A number of in-field sensing station are used for take samples of soil properties. The architecture of the sensing stations is deployment based on wireless link and bluetooth standard.
WSN Data	The data is provided by five in-field sensing stations. Each station is composed by data logging, power management system and wireless communication with bluetooth standard.
Kriging Contribution	Kriging is used for create (via estimation process) a spatial map of soil EC variation based on data provided by the in-field station.
Kriging Type	Undescribed.
Variogram	Undescribed.
Comments	The WSN architecture is deployment based on bluetooth standard. This architecture can be replace with Motes sensor nodes in order to improve the coverage area in a more efficient way saving time and energy resources. Moreover, with more samples locations will be possible create a more accurate spatial map of soil EC variations.

4.11 A real-time sensor network visualization system using KVS - Kyoto Visualization System (30)

Authors	Segawa, Norihisa and Yasuhara, Yukio and Sakamoto, Naohisa and Yoshihisa, Tomoki and Ebara, Yasuo and Koyamada, Koj.
Source	In proceedings, SenSys '07: Proceedings of the 5th international conference on Embedded networked sensor systems.
Publisher	ACM.
Year	2007.
Keywords	Visualization, isosurface, interpolation, Kriging method.
Field	Wireless Sensor Network, Real-Time Visualization, Interpolation, Isosurface.
Cited by	0, in Google Scholar.
Contribution	In this work is development a system that collects information from sensor nodes and is capable interpolate information on at any positions of space. Moreover, the data are visualize on real time by three dimensions on a computer.
Methodology	Experimental. The proposed systems is deployment in the Kyoto University Koyamada laboratory.
WSN Contribution	Used for the sensor information collection part. Mica2 and Micaz sensor are used for collect data.

WSN Data	This system works with mica (mica2 or micaZ) sensor nodes and an xserve data collection system of Crossbow. The system performs communication with xserve system by a socket, and collects sensor information by real-time.
Kriging Contribution	Used to interpolate data to continuous space.
Kriging Type	Undescribed.
Variogram	Undescribed.
Comments	It will be interesting see the application of this system in a more dense sensor nodes deployment area and analize what happen when a discontinuity over the space is introduced (e.g. a wall or other obstacle between sensor nodes).

4.12 Interpolation for Wireless Sensor Network Coverage (34)

Authors	Tynan, R. and O'Hare, G. M. P. and Marsh, D. and O'Kane, D.
Source	In proceedings, EmNets '05: Proceedings of the 2nd IEEE workshop on Embedded Networked Sensors.
Publisher	IEEE Computer Society.
Year	2005.
Keywords	Interpolation, Wireless Sensor Network Coverage, Energy Efficiency, Weighted Average Algorithm.
Field	Wireless Sensor Network, Coverage Problem, Node Scheduling, Energy Efficiency.

Cited by	13, in Google Scholar.
Contribution	In this work is proposed a technique based on interpolation with the aim to help to solve two common WSN problems: Network coverage and Node scheduling.
Methodology	Experimental. The proposed technique is applied on a real WSN.
WSN Contribution	The proposed method try to solve the WSN problems of network coverage and node scheduling in an energy efficient way.
WSN Data	Use 16 mica2 motes arranged in a regular 4x4 grid with a 4 inch vertical and horizontal separation between each node, and each node sampled its temperature sensor every minute.
Kriging Contribution	In the proposed technique, Kriging is not the interpolation method.
Kriging Type	Unsdescribed.
Variogram	Undescribed.
Comments	In this work is used Weighted Average Algorithm like interpolation method. However, another interpolation method may be used, e.g. Kriging.

Chapter 5

Comments about Kriging

"It is unwise to throw one's data into the first available interpolation technique without carefully considering how the results will be affected by the assumptions inherent in the method. A good GIS (Geographic Information System) should include a range of interpolation techniques that allow the user to choose the most appropriate method for the job at hand." (4)

Kriging is a stochastic spatial interpolation process. It is a well known and robust methodology broadly studied. Furthermore, has some advantages like: The variogram reflect the spatial correlation structure of the data and allow the compute of the weights in function of the empirical data; The estimators are unbiased, with minimum variance and accompanied by a measure of the error and associated confidence in each predicted value.

Despite Kriging's advantage some drawbacks can be mentioned. For example, if Kriging is compared with the deterministic spatial interpolation method: Inverse Distance Weighting IDW. These disadvantages include; Kriging techniques are more complex, demand several computational resources and require a careful selection of the variogram model. Furthermore, its structural analysis (variogram) can be a subjective process.

For further information, below are presented a very brief review of some works involving different spatial interpolation methods.

In (12) a novel alternative is proposed in order to improve the computation time requirements and memory resources for data sets from Kriging Systems with many observations using a Gaussian Markov random field on a lattice as an approximation of a Gaussian field.

In (17) is proposed an adaptive inverse-distance weighting method that take advantage of the computational simplicity of inverse distance weighting, but provide the additional flexibility to accommodate variability in the distance-decay relationship over the study area. This novel method is compared with ordinary Kriging.

In (33) a spatial evaluation of Mn from soils in citrus-growing areas was done through three estimation methods: Kriging, neural-fuzzy modeling and fuzzy interval arithmetic. The results show that the neuro-fuzzy hybrid method has produced more accurate outputs than Kriging.

The work in (6) describe the implementation and architecture of a Java-based intelligent advisor to assist a generic user, ranging from the casual to the specialist, in selecting the interpolation technique most appropriate for a given task and data set. The interpolation methods currently assessed by the system are multiple forms of Kriging, thin plate smoothing splines, inverse-distance weighting and trend surface/polynomial analysis.

In (10) data recovery and reconstruction methods for unsteady flow fields with spatio-temporal missing data are studied based on proper orthogonal decomposition (POD) and on Kriging interpolation. It is found that for sufficient temporal resolution, POD-based methods outperform Kriging interpolation. However, for insufficient temporal resolution, large spatial gappiness or for flow fields with black zones, Kriging interpolation is more effective. The results show that Kriging interpolation is an effective way of recovering missing data in unsteady flows even in sensitive regions, e.g., regions of absolute instability. For high temporal resolution (i.e., many snapshots), POD-based reconstruction is more accurate tan Kriging interpolation; however, for low temporal resolution Kriging is more effective. For small gappiness in the flow field, POD-based reconstruction is more accurate than Kriging; however, for large gappiness Kriging is more accurate.

In (3) is intends to show how the proper adjustment of variogram and Kriging parameters can be set to achieve quality results on resampling SRTM data (Shuttle Radar Topography Mission data) from 3” to 1” resolution. Examples are presented for a test area in western USA and include different adjustment schemes and comparisons with the original 1", with the national elevation dataset (NED), digital elevation model (DEM), and with other interpolation methods such as splines and inverse distance weighted. The results show that although the 1" surfaces resampled by Kriging and splines are very similar, the Kriging results are superior, since the spline-interpolated surface still presented some noise and linear artifacts, which were removed by Kriging.

In (36) a new method for studying spatial patterns is introduced, the two-dimensional net-function interpolation. The method can be used to interpolate unmeasured sample locations based on known values at nearby grid points. Specific examples from ecological studies in the Inner Mongolia Grassland, China are discussed to illustrate the use of the method. A brief comparison between the net-function interpolation and Kriging is also made. The results show that the net-function method, versus Kriging, appears to be undesirable for irregularly-gridded data. When anisotropy is taken into account with the universal Kriging algorithm, Kriging may become rather complex and computationally demanding.

The objectives of the study in (32) is to select an optimal interpolation method in the Minqin oasis (northwest China) region from among Kriging methods (including Ordinary Kriging, Simple Kriging, and Universal Kriging), the inverse distance weighting method, and the radial basis function method. These methods was compared via the interpolation accuracy of depth to groundwater and its estimation errors. The results show that Simple Kriging is the optimal method for interpolating depth to groundwater in this region (in terms of root mean squared errors and correlation coefficients between interpolated values and observed values).

Chapter 6

Final Remarks

The WSN are a *new* technology with a huge number of potential applications. The implementation of a WSN must tackle new challenges, problems and constraints such as the limited energy resources, limited process capabilities, topology changes, discrete data samples in time and/or space, among other problems.

In the other hand, Kriging technique is a spatial interpolation technique from the mining world that to extended its applications field to other earth sciences.

The application of Kriging technique in WSN problems and the way at which the Kriging technique and WSN are related in specific task systems was developed in this report through a literature research process. From the analyses over the selected works it can say that some works deal with specific WSN problems, mainly with energy efficiency issues, coverage holes, spatial localizations of the nodes, minimum number of sensors and sensor scheduling. Some of these problems are treated like optimization problems. In other works the Kriging predictions helps to create spatial interpolation maps that are useful to evaluated the spatial variation of a parameter under study. These maps have applications in different systems, e.g., precision agriculture systems.

Kriging was chosen like the interpolation technique for this survey because is a robust and well known interpolation technique that is based on the spatial correlation of the sample locations. Hence, it is capable to reach an acceptable estimation values with a measure of the estimation error. Some detractors affirm that Kriging is slow in delivering its results and needs too many calculation resources compared to other interpolation techniques. In case you would not trust the results obtained through Kriging, it remains always possible to use some other method of interpolation. If so, the results can then be compared through the error measurement of the predictions and the best method can be chosen for each particular application.

Future researches may extend this work considering how, for example, the higher density of sensors in an area can improve the accuracy of the Kriging predictions. Another option is to extend the predictions to time domain and estimate values between successive samples. Nevertheless, Kriging is not the only interpolation technique and other interpolation methods applied to WSN can be analyzed in future researches.

Appendix A

Example Details

A.1 s100: Dataset

```
$coords
               [,1]       [,2]                  [,1]       [,2]
  [1,] 0.807126710 0.94544601  [2,] 0.549998072 0.68326492
  [3,] 0.340805545 0.45850888  [4,] 0.137099310 0.47200832
  [5,] 0.044185692 0.12232017  [6,] 0.027816360 0.80374588
  [7,] 0.724385299 0.62332495  [8,] 0.246973875 0.14205770
  [9,] 0.522983879 0.76201844 [10,] 0.249600428 0.58405976
 [11,] 0.028991738 0.95606156 [12,] 0.143142421 0.95199657
 [13,] 0.086238803 0.14106986 [14,] 0.983920544 0.71920011
 [15,] 0.079471597 0.58686494 [16,] 0.478065402 0.43981990
 [17,] 0.631426017 0.89451549 [18,] 0.820550200 0.48675112
 [19,] 0.934560909 0.90151412 [20,] 0.094132199 0.55364481
 [21,] 0.585577094 0.69763691 [22,] 0.642417917 0.76206592
 [23,] 0.507945677 0.88213743 [24,] 0.363397676 0.62456433
 [25,] 0.513764089 0.06826610 [26,] 0.263806508 0.35663249
 [27,] 0.864579863 0.26637957 [28,] 0.005638006 0.76928547
 [29,] 0.907257782 0.13576162 [30,] 0.177797950 0.05321294
 [31,] 0.330195867 0.20887775 [32,] 0.094165342 0.77715519
```

```
[33,] 0.257783640 0.55595250 [34,] 0.226869478 0.59507909
[35,] 0.846112244 0.73963968 [36,] 0.404958459 0.05382997
[37,] 0.707190327 0.52866792 [38,] 0.732988894 0.60828701
[39,] 0.293062207 0.94696340 [40,] 0.192971485 0.07482082
[41,] 0.849779000 0.37836289 [42,] 0.457026324 0.35670797
[43,] 0.691539921 0.41060066 [44,] 0.475881600 0.68247605
[45,] 0.265413690 0.03265305 [46,] 0.679222414 0.43100733
[47,] 0.306418876 0.84172254 [48,] 0.108589044 0.72541736
[49,] 0.464779988 0.74625289 [50,] 0.968033380 0.94756137
[51,] 0.061719681 0.57977207 [52,] 0.306426739 0.90216261
[53,] 0.947014188 0.95192688 [54,] 0.430859474 0.96433238
[55,] 0.931844109 0.65749259 [56,] 0.689199685 0.15415125
[57,] 0.634984260 0.64798717 [58,] 0.485696871 0.40060389
[59,] 0.163376110 0.24714981 [60,] 0.887798236 0.38501224
[61,] 0.006870312 0.11247721 [62,] 0.447166599 0.62429936
[63,] 0.506515568 0.41561616 [64,] 0.967556274 0.58564516
[65,] 0.747906145 0.52078144 [66,] 0.503182120 0.45504266
[67,] 0.077190299 0.92241133 [68,] 0.588881995 0.83999337
[69,] 0.108194098 0.76308847 [70,] 0.886685456 0.83523563
[71,] 0.647070315 0.14569712 [72,] 0.290393424 0.60043479
[73,] 0.658765058 0.52603477 [74,] 0.748581991 0.26287565
[75,] 0.604099556 0.79045207 [76,] 0.851071746 0.76730799
[77,] 0.298447147 0.16615725 [78,] 0.020767781 0.98308196
[79,] 0.940281073 0.77707861 [80,] 0.586882023 0.70516562
[81,] 0.850595354 0.01091027 [82,] 0.381382126 0.99124979
[83,] 0.577533818 0.17780001 [84,] 0.158356967 0.20805035
[85,] 0.491523982 0.37358486 [86,] 0.733346733 0.38444906
[87,] 0.536329847 0.76250096 [88,] 0.900223871 0.82685943
[89,] 0.186263138 0.71121034 [90,] 0.904586329 0.95129012
[91,] 0.664045752 0.98082406 [92,] 0.085919891 0.68740117
[93,] 0.455045202 0.21624276 [94,] 0.890554640 0.94962814
[95,] 0.184807496 0.25771587 [96,] 0.585834014 0.44893034
[97,] 0.541334383 0.13499379 [98,] 0.406253994 0.96311050
```

```
 [99,] 0.495317768 0.17356993[100,] 0.385663031 0.52014266


$data
  [1]  0.917188752  1.148323354  1.032756300  0.121954767
       0.615298778 -0.550606543  1.703814887  1.747901020
       2.100869073  0.441224609 -0.009536357 -0.801448333
      -0.001930896  1.141943813  0.538675515  0.561124760
       1.084342606  1.494224867  1.451773709 -0.756622437
 [21]  1.742536841  1.972069943  0.869030503 -0.220931922
       1.311725186  1.561038129  1.843500850  0.333177663
       1.223030476  0.545023824  1.582932912 -0.814958051
       0.054556702  0.405697418  1.422665584  1.765298993
       1.185470638  1.754435368 -1.150624846  1.553357086
 [41]  1.164951011  0.259479909  1.577426439  0.837983077
       1.643087465  1.717231426  0.993917554  0.128603062
       0.805666518  0.765777025  0.103290499 -1.167695474
       0.719148783  0.359709271  1.778422657  2.079565424
       2.867896903  0.560021276  0.277490957  1.792041134
 [61]  0.200109632  0.237756326  1.308548621  1.944901149
       0.402131870  0.979640487 -0.238509435  2.156120583
      -0.610998066  1.546203174  1.496030375  0.353898003
       1.968717419  2.171577664  1.965981722  1.620228489
       1.637205070  0.061662135  1.810161014  1.726308891
 [81]  0.060908554 -0.729824032  1.210333642  0.643947930
      -0.066323182  1.162695117  2.443485524  1.845180798
       1.124844572  1.380025167  1.399538798  1.311149175
       1.606818085  1.429380087  0.134733580  1.284822319
       0.757246091  0.186184896  0.891084676  0.073563986


$cov.model
[1] "exponential"


$nugget
```

```
[1] 0

$cov.pars
[1] 1.0 0.3

$kappa
[1] 0.5

$lambda
[1] 1

attr(,"class")
[1] "geodata"
```

A.2 Empirical Variogram

```
> Vs100
$u
 [1] 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0

$v
 [1] 0.1730722 0.3376539 0.4521105 0.6099240 0.6075521 0.7320905
     0.9025480 0.8169235 1.0704021
[10] 1.0596945 0.8401933

$n
 [1]  45 250 446 640 684 717 655 517 449 323 139

$sd
 [1] 0.2230052 0.4518735 0.5850419 0.9622870 0.8918297 1.0145878
     1.0862696 0.9818199 1.1453274
[10] 1.0852590 0.8785460
```

```
$bins.lim
 [1] 1.00e-12 5.00e-02 1.50e-01 2.50e-01 3.50e-01 4.50e-01 5.50e-01
     6.50e-01 7.50e-01 8.50e-01
[11] 9.50e-01 1.05e+00

$ind.bin
 [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE

$var.mark
[1] 0.7322958

$beta.ols
[1] 0.930718

$output.type
[1] "bin"

$max.dist
[1] 1.05

$estimator.type
[1] "classical"

$n.data
[1] 100

$lambda
[1] 1

$trend
[1] "cte"
```

```
$pairs.min
[1] 2

$nugget.tolerance
[1] 1e-12

$direction
[1] "omnidirectional"

$tolerance
[1] "none"

$uvec
 [1] 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0

$call
variog(geodata = s100, uvec = seq(0, 1, l = 11), option = "bin",
    estimator.type = "classical")

attr(,"class")
[1] "variogram"
```

A.3 Model Variogram, Parameters Estimation Summary

```
> summary(mls100)
Summary of the parameter estimation
-----------------------------------
Estimation method: maximum likelihood

Parameters of the mean component (trend):
  beta
```

```
0.7766

Parameters of the spatial component:
   correlation function: exponential
      (estimated) variance parameter sigmasq (partial sill) =  0.7516
      (estimated) cor. fct. parameter phi (range parameter)  =  0.1827
   anisotropy parameters:
      (fixed) anisotropy angle = 0  ( 0 degrees )
      (fixed) anisotropy ratio = 1

Parameter of the error component:
      (fixed) nugget = 0

Transformation parameter:
      (fixed) Box-Cox parameter = 1 (no transformation)

Practical Range with cor=0.05 for asymptotic range: 0.5473499

Maximised Likelihood:
   log.L n.params      AIC      BIC
"-83.57"      "3"  "173.1"  "181.0"

non spatial model:
   log.L n.params      AIC      BIC
"-125.8"      "2"  "255.6"  "260.8"

Call:
likfit(geodata = s100, ini.cov.pars = c(1, 0.5), fix.nugget = T)
```

Bibliography

[1] Nadeem Ahmed, Salil S. Kanhere, and Sanjay Jha. The holes problem in wireless sensor networks: a survey. *SIGMOBILE Mob. Comput. Commun. Rev.*, **9**(2):4–18, 2005. 2.5

[2] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci. Wireless sensor networks: a survey. *Computer Networks*, **38**(4):393 – 422, 2002. 2.1, 2.2, 2.3, 2.4, 2.4

[3] C. H. Grohmann a;S. S. Steiner a. Srtm resample with short distance-low nugget kriging. *International Journal of Geographical Information Science*, **22**(8):895 – 906, 2008. 5

[4] P.A. Burrough. *Principles of geographical information systems for land resources assessment.* Oxford : Clarendon Press, 1992, Queen's Ln, Oxford OX1 4, UK, 1992. 5

[5] Alberto Camilli, Carlos E. Cugnasca, Antonio M. Saraiva, Andr R. Hirakawa, and Pedro L.P. Corra. From wireless sensors to field mapping: Anatomy of an application for precision agriculture. *Computers and Electronics in Agriculture*, **58**(1):25 – 36, 2007. Precision Agriculture in Latin America. (document), 4.6, 4.6

[6] William Cooper and Claire Jarvis. A java-based intelligent advisor for selecting a context-appropriate spatial interpolation algorithm,. *Computers Geosciences*, **30**(9-10):1003 – 1018, 2004. 5

[7] N. Cressie. *Statistics for Spatial Data.* John Wiley Sons, New York, NY, USA, 1993. 3.1, 3.3.1, 3.4

[8] Digital elevation models. GeoCommunity, March 2010. [online] http://data.geocomm.com/dem/. 4.2

[9] R. Graham and J. Cortes. Asymptotic optimality of multicenter voronoi configurations for random field estimation. *Automatic Control, IEEE Transactions on*, **54**(1):153–158, Jan. 2009. (document), 4.4, 4.4

[10] Hasan Gunes, Sirod Sirisup, and George Em Karniadakis. Gappy data: To krig or not to krig? *Journal of Computational Physics*, **212**(1):358 – 382, 2006. 5

[11] Brian Harrington, Yan Huang, Jue Yang, and Xinrong Li. Energy-efficient map interpolation for sensor fields using kriging. *IEEE Transactions on Mobile Computing*, **8**(5):622–635, 2009. (document), 4.5

[12] Linda Hartman and Ola Hssjer. Fast kriging of large data sets with gaussian markov random fields. *Computational Statistics Data Analysis*, **52**(5):2331 – 2349, 2008. 5

[13] C.B. Hedley and I.J. Yule. A method for spatial prediction of daily soil water status for precise irrigation scheduling. *Agricultural Water Management*, **96**(12):1737 – 1745, 2009. (document), 4.9

[14] Reiner Jedermann and Walter Lang. The minimum number of sensors — interpolation of spatial temperature profiles in chilled transports. In *EWSN '09: Proceedings of the 6th European Conference on Wireless Sensor Networks*, pages 232–246, Berlin, Heidelberg, 2009. Springer-Verlag. (document), 4.8, 4.9

[15] Yunseop Kim, R.G. Evans, and W.M. Iversen. Remote sensing and control of an irrigation system using a distributed wireless sensor network. *Instrumentation and Measurement, IEEE Transactions on*, **57**(7):1379–1387, July 2008. (document), 4.10, 4.9, 4.10

[16] D. Krige. *Master Thesis: A statistical approach to some mine valuations an allied problems at the Witwatersrand*. University of Witwatersrand, Johannesburg, South Africa, 1951. 3.1

[17] George Y. Lu and David W. Wong. An adaptive inverse-distance weighting spatial interpolation technique. *Computers Geosciences*, **34**(9):1044 – 1055, 2008. 5

[18] Liqian Luo, Aman Kansal, Suman Nath, and Feng Zhao. Sharing and exploring sensor streams over geocentric interfaces. In

GIS '08: Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems, pages 1–10, New York, NY, USA, 2008. ACM. (document), 4.1

[19] Morteza Maleki and Massoud Pedram. Qom and lifetime-constrained random deployment of sensor networks for minimum energy consumption. In *IPSN '05: Proceedings of the 4th international symposium on Information processing in sensor networks*, page 39, Piscataway, NJ, USA, 2005. IEEE Press. (document), 4.3, 4.3

[20] Postgraduate programmes 2009-2010, masters in advanced sciences of modern telecommunications. Programme offer academic year 2009-2010, December 2009. [online] http://www.uv.es/postgrau/pdf_en/advancedsciencesofmoderntelecommunications.pdf. 1

[21] B. Matern. *Spatial Variation.* Statens Skogsforsnings Institut, Stockholm, Sweden, 1960. 3.1

[22] G. Matheron. Traite de geostatistique appliquee, tome i. *Memoires du Bureau de Recherches Geologiques et Minieres*, (14), 1962. 3.1, 3.3, 3.3.1, 3.4

[23] G. Matheron. Principles of geostatistics. *Economic Geology*, (58):1246–1266, 1963. 3.1, 3.4

[24] G. Matheron. Traite de geostatistique appliquee, tome ii: Le krigeage. *Memoires du Bureau de Recherches Geologiques et Minieres*, (14), 1963. 3.1

[25] D. Hawkins N. Cressie. Robust estimation of the variogram. *Mathematical Geology*, **12**:115–125, 1980. 3.3.1, 3.5.2

[26] Costas Pontikakos and Theodore Tsiligiridis. *New Technologies, Mobility and Security*, chapter 48, pages 583 – 595. 4.7

[27] Costas M. Pontikakos, Theodore A. Tsiligiridis, and Maria E. Drougka. Location-aware system for olive fruit fly spray control. *Computers and Electronics in Agriculture*, **In Press, Corrected Proof**:–, 2009. (document), 4.7, 4.7

[28] R Development Core Team. *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria, 2006. ISBN 3-900051-07-0. 3.5.2

[29] P.J. Ribeiro Jr. and P.J. Diggle. geoR: a package for geostatistical analysis. *R-NEWS*, **1**(2):15–18, 2001. 3.5.2

[30] Norihisa Segawa, Yukio Yasuhara, Naohisa Sakamoto, Tomoki Yoshihisa, Yasuo Ebara, and Koji Koyamada. A real-time sensor network visualization system using kvs: Kyoto visualization system. In *SenSys '07: Proceedings of the 5th international conference on Embedded networked sensor systems*, pages 367–368, New York, NY, USA, 2007. ACM. (document), 4.11, 4.11

[31] H. S. Sichel. An experimental and theoretical investigation of bias error in mine sampling with special reference to narrow gold reefs. *Trans. Inst. Min. Metall.*, **56**:403–473, 1947. 3.1

[32] Yue Sun, Shaozhong Kang, Fusheng Li, and Lu Zhang. Comparison of interpolation methods for depth to groundwater and its temporal and spatial variations in the minqin oasis of northwest china. *Environmental Modelling Software*, **24**(10):1163 – 1170, 2009. 5

[33] B. Tutmez, A. Dag, H. Erdem, and B. Torun. Evaluation of mn concentration provided by soil in citrus-growing regions. *Computers and Electronics in Agriculture*, **67**(1-2):27 – 34, 2009. 5

[34] R. Tynan, G. M. P. O'Hare, D. Marsh, and D. O'Kane. Interpolation for wireless sensor network coverage. In *EmNets '05: Proceedings of the 2nd IEEE workshop on Embedded Networked Sensors*, pages 123–131, Washington, DC, USA, 2005. IEEE Computer Society. (document), 4.12, 4.12

[35] Muhammad Umer, Lars Kulik, and Egemen Tanin. Kriging for localized spatial interpolation in sensor networks. In *SSDBM '08: Proceedings of the 20th international conference on Scientific and Statistical Database Management*, pages 525–532, Berlin, Heidelberg, 2008. Springer-Verlag. (document), 2.5, 4.2, 4.2

[36] Jianguo Wu. A method for studying spatial patterns: The netfunction interpolation. Technical report, Ithaca, NY, USA, 1993. 5

[37] Jennifer Yick, Biswanath Mukherjee, and Dipak Ghosal. Wireless sensor network survey. *Computer Networks*, **52**(12):2292 – 2330, 2008. 2.1, 2.2, 2.3, 2.4