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Alternatives for Geosensors Networks Data Analysis

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Abstract. *Geosensors networks are dense wireless networks of small, low-cost sensors, which collect and disseminate environmental data of a vast geographical area. These networks hold the promise of revolutionizing sensing in a wide range of application. Despite the large amount of research in this field, little effort has been done to establish how to deal with the data collected by these networks. This paper examines this emerging subject and identifies alternatives for geosensors data analysis.*

1. Introduction

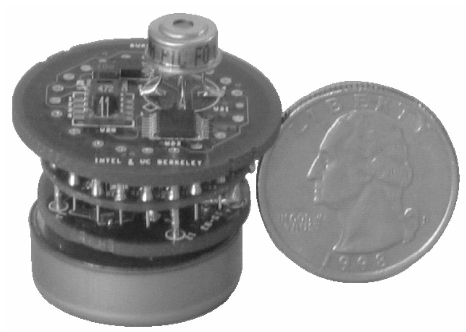
The comprehension of the physical world is a constant concern of the human species. This knowledge demand has been impelling researchers to install devices capable to collect data about several environments including vast geographical areas.

Despite its frequency, phenomena monitoring in large geographical areas is still a costly and difficult task. The observation structures are expensive and demand constant maintenance. Moreover, they cannot be deployed in any place, making unfeasible the proper covering of the study area. Frequently, the temporal resolution of the collected data is not large enough to understand the phenomenon. However, a new technology promises to help the physical world observation: the sensors networks.

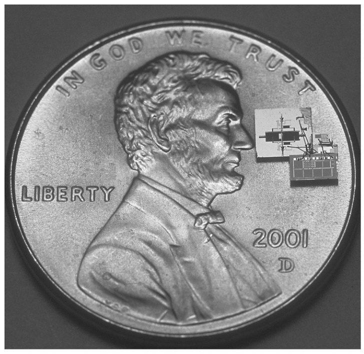
Sensors are small electro-mechanical devices that can measure environmental characteristics like temperature, pressure, humidity and infrared light, for instance. Figure 1 shows two examples of sensors. These devices communicate with each other over a wireless network and form a sensors network. When they are deployed over a geographic area and collect data whose geospatial information is important, they form a geosensors network (Nittel and Stefanidis, 2005). The prefix *geo* is just to emphasize the geographical aspect of the network.

Geosensors networks have a wide range of applications (Xu, 2002). They go from natural disasters detection to data collection for retrospective studies, going by traffic organization, intelligent houses and the study of ecosystems and animal life sensitive to the human presence (Mainwaring et al., 2002).

Although it is a new research area, much work has been done, mainly in data routing, which is the way the data are transported along the network until the user. However, to the best of the author's knowledge, there is not much concern about how to analyze these data. The main goal of this paper is to identify alternatives for the analysis of data collected by a geosensors network considering the peculiarities of this instrument.



MICA-2



Smart Dust prototype

Figure 1 – Two examples of sensors: MICA-2 (by Intel and University of California- Berkeley) ; Sensor prototype of Smart Dust Project (Kahn et al., 1999)

2. Geosensors networks characteristics

The basic functioning of a geosensors network is presented in Figure 2. Sensor nodes collect data on sensor field, process these data and send them to other sensor nodes or to a special node called sink. Then, data are sent to the gateway, which communicates with a base station through the Internet or a satellite. The user has access to the base station, which can be a desktop computer.

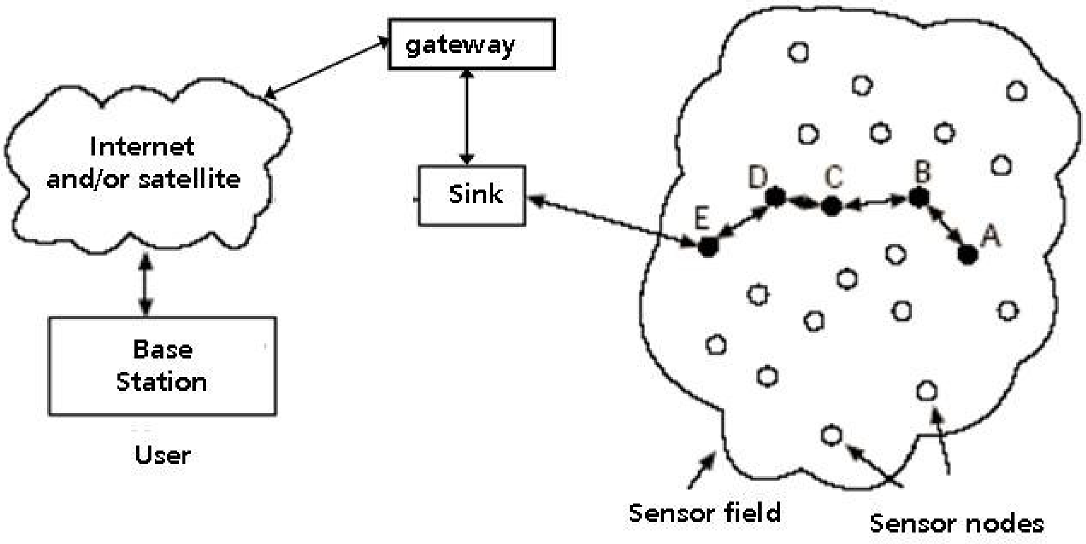


Figure 2 - Schematic representation of a geosensors network (adapted from Akyildiz et al., 2002)

The networks currently deployed are still experimental and have some dozens of nodes, whose installation is made manually. However, foreseen decrease of the components cost will enable the deployment of thousands of nodes, which will be done by an airplane, for example. This will allow deploying networks in inhospitable or dangerous areas. Once installed, the nodes must use their self-organization ability to detect their neighbors and build the network topology.

Geosensors *must* know their geographical location and that is a crucial point for geosensors networks. According to Ratnasamy et al. (2002), a sensor network data is useful only if the location of its source is known. Certainly, sensors nodes can not afford a Global Positioning System (GPS), because it still spent a lot of power. However, some research has been done to design low-power GPS receivers (Meng, 1998), which will enable the GPS receivers to become affordable to some types of sensors nodes. Nowadays, if the nodes deployment is made manually, one can use the GPS to achieve their geographical locations. When this is not possible, the alternative can be the recursive trilateration/multilateration techniques as those ones described by Bharathidasan et al. (2003) or the algorithms proposed by Bulusu et al. (2000). They use the inherent radio-frequency communications capabilities of the geosensors and just require a set of references points with known location.

One of the most important characteristics of geosensors networks is their nodes limitation in power, computational capacities, and memory. The power limitation is the most critical.

After collect the data, the nodes have to send them to the base station using a multi-hop path along the network (Figure 2). This task is called *data routing* and involves communication between nodes. According to Potie and Kaiser (2000), the communication task is the one that consumes more energy, much more than data processing.

Therefore, in order to save energy, some routing protocols propose data preprocessing during its transportation to the base station. Data aggregation is an example of preprocessing. The aggregation consists in calculating a summary (counting, average, median, minimum or maximum). One of the routing protocols using data aggregation is called Low-Energy Adaptive Clustering Hierarchy - LEACH (Heinzelman et al, 2000). The LEACH´s idea is to form clusters of nodes before each data transmission. The components of a cluster choose a node to be the cluster head and send their data to it. This cluster head computes the aggregation of these data and sends the summary to the gateway. This reduces the number of transmissions, avoiding that each node has to route its data to the gateway. The data aggregation should preserve the location of the nodes whose data were aggregated, because the geographical information is important in a geosensors network.

Akkaya and Younis (2004) discuss other routing proposals and their mechanisms to save energy.

3. Statistical analysis of geosensors networks data

Geosensor networks open the possibility of a detailed vision of the physical world. However, "the overwhelming volume of observations produced by these sensors is both a blessing and a curse", as Ratnasamy et al. (2002) well said about data routing. This statement is also valid for data analysis. How to deal with so many data?

Considering the application that has driven the geosensors network project, two types of data analysis can be identified: instantaneous and retrospective.

3.1 – Instantaneous analysis

The instantaneous analysis involves immediate decision based on the results and it must happen as soon as the data are available. Instantaneous analyzes are necessary in the monitoring applications. For instance, consider the task of detecting forest fires. The continuous arrival of temperature data considered high in a certain area, as well data pointing to low humidity or smoke presence, certainly it will take to the conclusion there is a fire focus in that area or close to. The instantaneous analysis can use data mining techniques to identify patterns and outliers values, one of the most important tasks in monitoring applications.

Mining data means to analyze them in great groups with the objective of summarizing them and to find hidden relationships in a comprehensible and useful way for the analyst (Hand et al., 2004). Data mining uses the theory of probabilities, algorithms of machine learning and also statistical techniques, as regression analysis and maximum likelihood estimation.

After the instantaneous analysis, one can discard the data or store them for a retrospective analysis. Another alternative is to keep data on the events detected to build a knowledge basis for the monitored phenomenon.

3.2 – Retrospective analysis

In retrospective studies, the main interest is the analysis of historical series, through its description and modeling, allowing the prediction of future observations.

Considering the geographical nature of the geosensors networks and that each geosensor is a punctual source of data, it is natural to imagine that these data can be treated as spatially continuous, one of the four data classes in Spatial Statistics (Bailey and Gatrell, 1995). The spatially continuous data are the result of random variables observed in points of known location in the geographical space. Formally, $Z(x_i,y_i,t)$ is a random variable observed in the point i, which has coordinates $(x_{i,}y_i)$, at the time period t. The group of variables $Z(x_i,y_i,t)$, (i=1,2,...,n) and (t=1,...,m), can be seen as a random field, a collection of interdependent random variables that have a spatio-temporal component (Guttorp, 1995).

A static geosensors network has points whose coordinates are fixed and known, that is, the points (x_i,y_i) are the same at each time period t. Each measurement generates the realization of a two-dimensional random field, temporally correlated among them. These realizations can be seen as a collection of random fields or as a three-dimensional random field, in which the time is the third dimension. The data generated by the measurement are spatially continuous.

In dynamic networks, the geosensors must register the phenomenon data, the time and also its geographical location. Differently of the static networks, the points (x_i,y_i) change at each time period. The data collected by a dynamic network can be considered spatially continuous, since the study interest is not the spatial pattern of the sensor nodes, but their measured values. In other words, the geographical position of the sensor node is considered known and not as a random component. Otherwise, the data should be analyzed as point patterns (Bailey and Gatrell, 1995).

The techniques used in spatially continuous data analysis are known as Geostatistics and kriging is the most popular of them. In the most general model, universal kriging, the random field Z can be described as below

$$Z(x_i,y_i)=\mu(x_i,y_i)+U(x_i,y_i)+e(x_i,y_i)$$, for a time period t,

where $\mu(x_i,y_i)$ is the mean of the process and it can be modeled with covariates;

$U(x_i,y_i)$ is a spatially structured random effect and

$e(x_i,y_i)$ is a white noise, that is, it has a Gaussian distribution with zero mean and constant variance and they are uncorrelated. It is known as nugget effect.

In the ordinary kriging, $\mu(x_i,y_i)$ is considered constant for the whole region. The objective of kriging is to estimate Z in an unobserved point $s=(x_s,y_s)$, in other words, $Z(x_s,y_s)$.

In Classical Statistics approach, the covariance matrix of $U(x_i,y_i)$ is modeled. Usually, a function of the Matèrn family is adopted. Using this model, one can calculate the estimates for the covariance between the observed points and a point $s=(x_s,y_s)$ for which one want to estimate Z. These estimates, the covariance matrix and $\mu(x_i,y_i)$ estimates allow the estimation of $Z(x_s,y_s)$ (Isaaks and Srivastava, 1990).

Bayesian Statistics considers the parameters as random variables and makes inferences about them by using a posterior probability distribution (Carlin and Louis, 1996). One calculates this *posterior distribution* by combining a prior knowledge and the sample information through the Bayes theorem. A probability distribution expresses this prior knowledge (the parameter *prior distribution*) and the *likelihood function* expresses the sample information.

In the Bayesian approach for kriging, the covariance matrix of $U(x_i,y_i)$ is modeled jointly with the other parameters, resulting in the *posterior* distribution of these parameters (Diggle et al., 1998). The prediction of Z for unobserved points is made by *predictive distributions*. They are calculated from the posterior distribution of the parameters in the Z model. The punctual estimate of the Z value is given by a summary of the predictive distribution, for instance, the average. Kitanidis (1986) showed that the classical approach for kriging is a special case of the Bayesian approach in which there is a *prior* ignorance on the trend surface parameters.

3.2.1 – Incorporating the time into the data analysis

The temporal component is still a challenge in the spatially continuous data analysis (Schmidt et al., 2002). The problem is to find out a covariance structure that describes the spatial correlation between two localizations for each instant of time.

The simplest proposal is to obtain the covariance structure multiplying the spatial covariance by the temporal covariance,

$$Cov[Z(x_i,y_i,1),Z(x_j,y_j,2)] = Cov[Z(x_i,y_i),Z(x_j,y_j)] \times Cov[Z(1),Z(2)].$$

When this type of covariance structure holds, the process $Z(x_i,y_i,t)$ is said to be *separable*. Likewise in the case of spatial covariance, suitable forms for the functions of spatial and temporal covariance can be adopted (Matèrn family, for instance). However, this separable form for the spatio-temporal covariance structure demands the supposition that $Cov[Z(x_i,y_i,1),Z(x_j,y_j,2)] = Cov[Z(x_j,y_j,1),Z(x_i,y_i,2)]$, what doesn't seem reasonable for most of the studied phenomena. Suppose, for instance, that Z is the atmospheric temperature and the points $i=(x_i,y_i)$ e $j=(x_j,y_j)$ belong to the path usually made by the cold fronts coming from Argentina. If the front goes from i to j, it is reasonable to think that a temperature decrease in i at time 1 will be related to a temperature decrease in j at time 2. However, this won't implicate that a temperature decrease in j at time 1 will be related to a temperature decrease in i at time 2.

Some authors proposed *non-separable* spatio-temporal covariance functions that are useful for modeling. Gneiting (2002), for example, developed a class of non-separable covariance functions.

An alternative to spatio-temporal data analysis is the space-time Kalman filter (Cressie and Wikle, 2002). Writing $\mathbf{Z_t} = [Z(x_1,y_1,t), Z(x_2,y_2,t), \ldots, Z(x_n,y_n,t)]$, the column vector that contains the data for the n areas in the time t, one can express the process $\mathbf{Z_t}$ as below

$$\mathbf{Z_t} = F'_t\boldsymbol{\beta_t} + \boldsymbol{\varepsilon_t}, \qquad \boldsymbol{\varepsilon_t} \sim \text{Gaussian}\,(\mathbf{0},V_t) \qquad (1)$$

$$\boldsymbol{\beta_t} = G_t\boldsymbol{\beta_{t-1}} + \boldsymbol{\omega_t}, \qquad \boldsymbol{\omega_t} \sim \text{Gaussian}\,(\mathbf{0},W_t)\ ,\ t = 1,2,3,\ldots T. \qquad (2)$$

The equations (1) e (2) compose the space-state model. The observation equation (1) relates the data $\mathbf{Z_t}$ to an unobserved state vector $\boldsymbol{\beta_t}$ with p elements. The evolution equation (2) links the states over time. The vectors $\boldsymbol{\varepsilon_t}$ and $\boldsymbol{\omega_t}$ have n and p elements, respectively, and represent the error terms in each model equation, with covariance matrices V_t and W_t. The matrices F_t and G_t are the design and evolution matrices, respectively. A simple approach sets $F_t = I_n$, $G_t = I_n$, $V_t = I_n$ and puts the spatial covariance structure in W_t . The space-state model can be cast in the bayesian framework. Adopting the Gaussian probabilistic model, the posterior distribution of $\boldsymbol{\beta_t}$ is Gaussian with mean $\mathbf{m_t}$ and covariance matrix C_t, where $\mathbf{m_t} = \mathbf{m_{t-1}} + A_t(\mathbf{Z_t} - \mathbf{m_{t-1}})$ and matrices C_t and A_t are the result of operations with the matrices F_t, G_t, V_t and W_t. The term "filter" refers to a recursive procedure for inference about the state vector $\boldsymbol{\beta_t}$: the knowledge about $\boldsymbol{\beta}$ at time t-1 ($\mathbf{m_{t-1}}$) is updated at time t through the observation of $\mathbf{Z_t}$, resulting in the knowledge about $\boldsymbol{\beta}$ at time t ($\mathbf{m_t}$). Applications of this technique can be found in Stroud et al. (2001) and Wikle and Cressie (1999), just to cite a few examples.

Space-time Kalman filter is a very flexible framework to data analysis. One of its flexible characteristics is the size of data vector $\mathbf{Z_t}$, which has not to be the same every time period t. This fits very well to the geosensors network data, since sensors can fail to transmit their data at some time period.

3.2.2 - Aggregated data analysis

The transportation of all nodes data can spend much energy, especially in the case of densely deployed geosensors networks. As seen previously, the aggregation of these data is one of the strategies used in routing protocols to save energy. Since the data are associated to the aggregator node, from the data analysis point of view, the points configuration presented in the Figure 3a (complete network) would become the points configuration of the Figure 3b (network reduced to the aggregator nodes). This reduction of the points number would be compensated by a decrease in the noise present in the data, a variability source that doesn't interest to the analyst. The data could still be treated as spatially continuous.

Another approach for the data analysis is to consider that each aggregator node is responsible for an area. This area is the union of the areas nodes under the aggregator node jurisdiction (Figure 3c). The area of a node can be obtained by Dirichlet tessellation, in case the location of the nodes that sent their data to the aggregator node is preserved. In this approach, the aggregated data is associated to an area and no more to a point. Hence, it should be treated as an area data, other Spatial Statistics class of data.

Area data are quite frequent in the Spatial Epidemiology, especially in disease risk maps (Bailey, 2001). Bayesian inference has become a common approach in space-temporal modeling of area data.

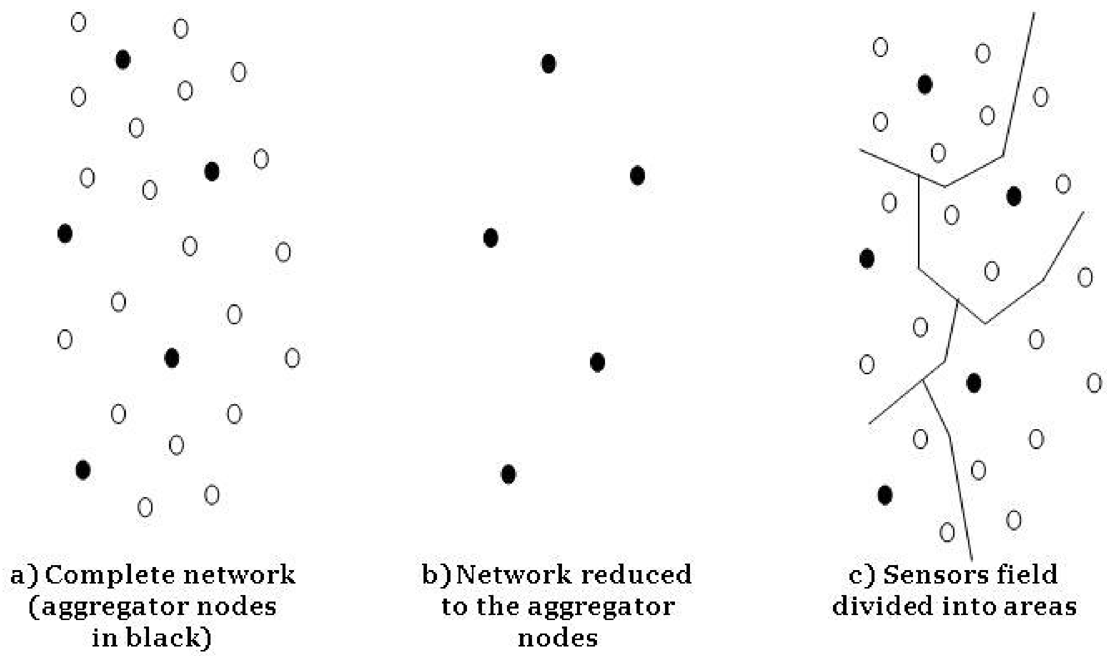


Figure 3 –Geosensors network with in-network data aggregation

The variable $Z(x_i,y_i,t)$ assumes a probabilistic model with mean μ_{it} and variance σ^2_{it}, and its mean is modeled. One of the spatio-temporal models for μ_{it} is:

$$f(\mu_{it}) = \alpha + \varphi_i + \nu_i + \delta_0 t + \delta_i t, \quad i=1,\ldots,n \text{ e } t=1,\ldots,m. \qquad (3)$$

where f(.) is a function whose values are real numbers; n is the number of areas; m is the number of time periods ; α is the component of $f(\mu_{it})$ that is common to all areas and time periods; φ_i and ν_i are the spatially unstructured and structured components of

$f(\mu_{it})$, respectively; δ_0 is the temporal coefficient spatially unstructured and δ_i is the temporal coefficient spatially structured.

The spatial structure enters the model through the prior distributions of ν_i and δ_i, as present below

$$\nu_i | \nu_{j \neq i} \sim Gaussian\left(\frac{\sum_{j \neq i} w_{ij} \nu_j}{\sum_{j \neq i} w_{ij}}, \frac{\sigma_\nu^2}{\sum_{j \neq i} w_{ij}} \right) \qquad \delta_i | \delta_{j \neq i} \sim Gaussian\left(\frac{\sum_{j \neq i} w_{ij} \delta_j}{\sum_{j \neq i} w_{ij}}, \frac{\sigma_\delta^2}{\sum_{j \neq i} w_{ij}} \right)$$

where w_{ij} are suitable adjacency weights for the areas.

The model for ν_i and δ_i prior distributions is called Gaussian Conditional Auto Regressive (CAR). It conditions the mean of the area on its neighbors' values using a weighted average. The parameters σ_ν and σ_δ control the strength of local spatial dependence. Inferences about each parameter are made using samples of its posterior distribution. These samples are obtained by Markov Chain Monte Carlo simulation (Gamerman, 1997). If ν_i assumes values close to zero with large probability, this means that the neighborhood of area i doesn't have influence on its mean. The same is valid for δ_i, what indicate that the neighborhood of area i doesn't have influence on temporal component of the trend μ_{it}.

The options usually adopted for the other prior distributions are: α ~ Uniform [$-\infty$;$+\infty$]; δ_0 ~ Uniform [$-\infty$;$+\infty$] ; φ_i ~ Gaussian ($0;\sigma^2_\varphi$)

The model in (3) can include covariates, allowing the study of other variables measured by the same sensor node. An alternative to the Bayesian approach when there are covariates is to use the Geographically Weighted Regression (GWR - Brunsdon et al., 1998). The idea of GWR is to estimate the regression coefficients for each area using their neighbors as data entry in a weighted regression. The weights are defined as a function of the distance to the possible neighbors. Each period time is modeled separately.

A third alternative for area data analysis is the space-time Kalman filter framework (Rojas and Ferreira, 2004). The approach is very similar to that adopted for spatially continuous data.

From statistical point of view, treating the aggregated data as if it was an area data is the most appropriate approach. That is because the aggregated data is not just composed by the data of the aggregator node, but also for a combination of its neighbors' data.

However, it is necessary to be careful about the definition of the areas, because the analysis results will be associated to them. The proposal of sensors data storage done by Goldin and Kutlu (2004) establishes that areas of interest are defined in a geographical database and the sensors data are aggregated according these areas. The routing protocol LEACH-C (Heinzelman et al., 2002) proposes the aggregator nodes (cluster heads) are chosen in the base station. As a modification of this proposal, the choice process could include some geographical parameter so that the clusters are well distributed in geographical terms. The aggregation could also be defined in several levels, from a less aggregated level (many clusters) until a more aggregated level (few clusters). In Goldin and Kutlu proposal as well in the LEACH-C modification, the analyst would have more control over his or her analysis areas.

As the networks size increases, sending all data to the base station become unfeasible. Networks that have to send their data continuously have few options to save energy. One of them is to aggregate the data. However, data aggregation can be good in terms of analysis, because it helps to reduce the noise level, avoiding uninteresting variability sources.

4. Concluding Remarks

Geosensor networks promise a revolution in the physical world observation, offering the possibility of a dense sensing of the environment. This technology will provide an unprecedented amount of detailed measurements over wide geographic areas. While a considerable amount of research has been made to enable the data collection and data delivery, little effort has been done towards the analysis of these data.

In this scenery, this work tried to identify the analysis types to which the geosensors data can be submitted. Techniques as data mining and spatial statistics were chosen and discussed in this context. The data aggregation, which is thoroughly proposed to save the network energy in the data routing stage, it was also evaluated in the data analysis context. Considering dense networks, as the ones that are foreseen for the future, the aggregation can also help to improve the data quality, eliminating the variability due to uninteresting sources.

In addition to help the geosensors data analysis, spatial statistics methods, specially geostatistical techniques, can be useful to solve the design network problem: how to choose the best locations for the geosensors deployment. Some approaches consider the prediction variance of kriging estimates as a reasonable measure of the goodness of a spatial sampling scheme (Bogárdi et al., 1985 ; Trujillo-Ventura and Ellis, 1991; as a few examples). As might be expected, the deployment of the geosensors has to be done manually to satisfy the solution found by these methods.

Sensors networks are a new research subject and much more work has to be done to solve problems like energy efficiency, nodes localization and data routing, for example. Despite their currently limitations, sensors networks still have many contributions to offer to environmental monitoring and surveillance applications.

5. Acknowledgements

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