

On GeoSensor Network optimization using a model-based approach

Alexander C. Walkowski

Institute for Geoinformatics, University of Münster
walkowski@uni-muenster.de

Abstract. The presented model-based approach comprises of a phenomenon model and a model of the mobile geosensor network (GSN). The phenomenon model estimates the characteristics of the observed phenomenon by means of a geostatistical approach. Based on this phenomenon model it is determined where additional information is needed. Also the limitations and constraints of the GSN are taken into account during the optimization process. Therefore, we use Hägerstrand's time geography, which allows modeling the potential activity area of the geosensor nodes. The potential activity area of a geosensor node is the area in which it can operate. Existing optimization methods are either based on geometric considerations like coverage and exposure based approaches or communication and energy based approaches. The presented approach combines the existing technologies of kriging and time geography in order to come up with a holistic optimization method. A table top experiment proved the efficiency of the model-based approach.

1 INTRODUCTION

The advancing development of sensor technologies revolutionizes the way of capturing data about spatio-temporal phenomena. Currently, a change from a centralized approach based on isolated sensors to an approach using distributed sensors is performed (Nittel and Stefanidis 2005). This increases the importance of monitoring network optimization in order to enhance efficiency. Existing approaches for optimizing monitoring networks are suited for optimizing GSN only to a limited extend. Coverage oriented methods for example do not take into account the realization of the dynamic phenomenon and thus do not adapt the monitoring network to processes like the dispersion of toxic plumes. Both, the characteristics of the phenomenon and those of the geosensor network (GSN) have to be taken into account while optimizing mobile GSN.

The rest of the paper is structured as follows: First the term geosensor network is defined. Subsequently the model-based approach is presented (section 3) and is evaluated by means of a table top experiment (section 4). Finally, a conclusion and an outlook on potential future developments are given.

2 GEOSENSOR NETWORKS

The advancing development of sensor technology especially in the field of micro-electro-mechanical-systemy (MEMS) yields in a miniaturization of sensors. These developments enable the construction of *sensor nodes* comprising of (wireless) communication device, memory, processor and power source (see Figure 1). Small sensor nodes enable the construction of new sensor networks with an unprecedented network density (Warneke 2006:1).

Iyengar et al. (2004:483) define the term *distributed sensor network* (DSN) as a collection of a large number of heterogenous intelligent sensors which are distributed geographically over an environment and connected through a communication network. Other authors – like Römer and Mattern (2004:54f.) – emphasize the wireless communication and use the term *wireless sensor network* (WSN). In our opinion both terms are interchangeable, because wireless communication is essential for mobile networks (Karl and Willig 2005:2). DSN are for example used in building automation, medical-care applications and control of manufacturing (Akyildiz et al. 2002:395ff.). It is typical for DSN applications that the sensor nodes are not explicitly georeferenced. The explicit georeferencing of the sensor nodes yields in the definition of a geosensor network. Nittel and Stefanidis (2005:2) define GSN as a “sensor network that monitors phenomena in geographic space, and in which the geospatial content of the information collected, aggregated, analyzed, and monitored by a sensor network is fundamental.” In our opinion it is not clear from this definition, why a DSN without georeferenced sensor nodes is not a GSN. Thus we define a *geosensor network* (GSN) as a specialized sensor network comprising of georeferenced *geosensor nodes*. If the geosensor nodes are actively or passively moving through the space they form a *mobile geosensor network*.

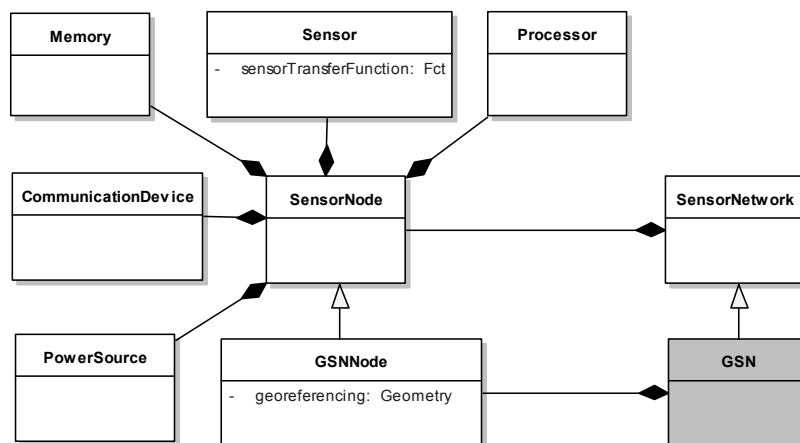


Figure 1: Components of a geosensor network

3 MODEL-BASED APPROACH

The model-based approach combines a phenomenon model with a GSN model in order to optimize the monitoring network. The workflow of the model based approach is shown in Figure 2. A short description of the GSN model respectively phenomenon model is given in the following subsections.

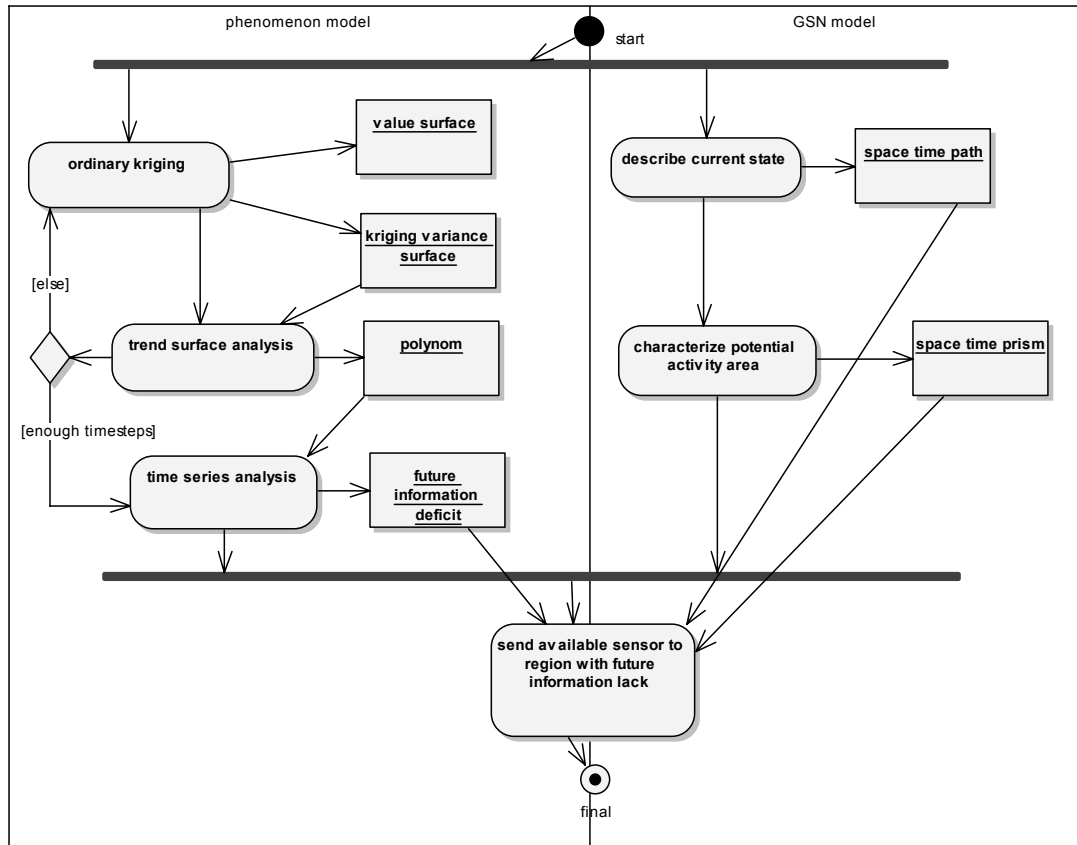


Figure 2: Activity diagramm of the model-based optimization approach

3.1 Phenomenon Model

In the context of this paper it is assumed that all observations (samples of the regionalized variable) are propagated to a base station which computes a model of the monitored phenomenon. The model – computed from the values $z(t_j)$ observed by the GSN at the point in time t_j – represents the continuous *value surface*. For the generation of the model kriging methods are used (Cressie 1993), which yield not only in the value surface, but also in the kriging variance that determines the *lack of information* at each point in the area of interest for the time t_j . If the optimization of the GSN would be performed only on the basis of this information, the dynamic of the phenomenon would not be taken into account. The optimization would be based solely on the lack of information at t_j . Instead the following approach

is used: Based on the method of trend surface analysis (TSA) a two dimensional polynomial is fitted to each of the last n kriging variance fields. This results in a vector (time series) for each parameter of the polynomial. In the next step we apply time series analysis tools to the parameter vectors in order to forecast the parameter values. The choice of method depends upon the length of the time series. For short time series simple trend models will be applied; for longer time series Box-Jenkins (Box et al. 1994) models might be used. Based on the predicted parameters of the polynomial for time t_{j+1} a surface of the *future information deficit* is computed.

The surface of the future information deficit allows for the identification of sensors which are able to reach the centers of regions with a high lack of information. These regions are defined as areas in which the information deficit exceeds a predefined threshold. Thus the network constellation will be adapted in order to minimize the (future) information deficit.

3.2 GSN Model

A simple GSN optimization approach would send the geosensor node which is the closest one to the area with a high lack of information. But this approach is not suited for heterogeneous GSN which may consist of mobile and stationary geosensor nodes. Additionally this approach does not take into account spatiotemporal waypoints. This means that geosensors nodes may have to execute measurements at defined locations at certain points in time. Thus spatiotemporal waypoints limit the radius where geosensor nodes are able to move to. As a result the determination of the geosensor node that is best suited for moving into a region with a lack of information is more complicated. Using the concepts of Hägerstrand's time geography (Hägerstrand 1970), it is possible to determine those geosensor nodes that are able to reach the centre of a region with a high lack of information (R_{IM}). This is the case if the centre of R_{IM} lies within the time-space-prism of a geosensor node. If the centre of R_{IM} is contained in the space-time-prisms of more than one geosensor node it is necessary to select the geosensor node that has to cover the smallest distance. Thus it is ensured that the GSN is optimally organized using a minimal amount of energy.

4 TABLE TOP EXPERIMENT

In order to test the presented approach a spatiotemporal phenomenon was simulated by means of a table top experiment. The dispersion of a toxic plume was simulated by trickling red ink on a 50 by 50cm plane covered with a water film. The current of the water film imitates the drift of the toxic plume in the direction of the wind. We took every three seconds a

picture of the plane, representing the population that is sampled by 100 geosensor nodes. At the beginning of the test, the geosensor nodes were placed randomly. They observe the concentration of the red ink by evaluating the RGB color space.

The observations were fed into the phenomenon model, resulting in a surface representing the phenomenon and a surface of the information deficit (kriging variance). After an initialization phase of n time steps the optimization was executed for the first time. That means the future information deficit was predicted and one geosensor node was relocated based on the GSN model. In this first evaluation the GSN model was not implemented as a software module, but was executed manually. Figure 3 depicts some exemplary results.

The first row shows values observed by 100 geosensor nodes for three points in time. For t_n the geosensor nodes were located randomly, but they were not moved from t_n to t_{n+5} . The phenomenon model – shown in the second row – was calculated by means of an ordinary kriging, which allows for the computation of the information deficit (kriging variance), depicted in the third row. The last row in Figure 3 lists the results of a trend surface analysis for the information deficit. Based on the future information deficit – shown in the third cell of the last row in Figure 3 – the geosensor network is optimized. In this evaluation procedure it was assumed that only the geosensor node marked by a circle could be relocated (see second cell of the first row in Figure 3). All others are either fixed, or have spatiotemporal waypoints, which prohibit a relocation of the geosensor node into the region with high information deficit. In the last column the optimized GSN, the resulting phenomenon model, and the information deficit are presented.

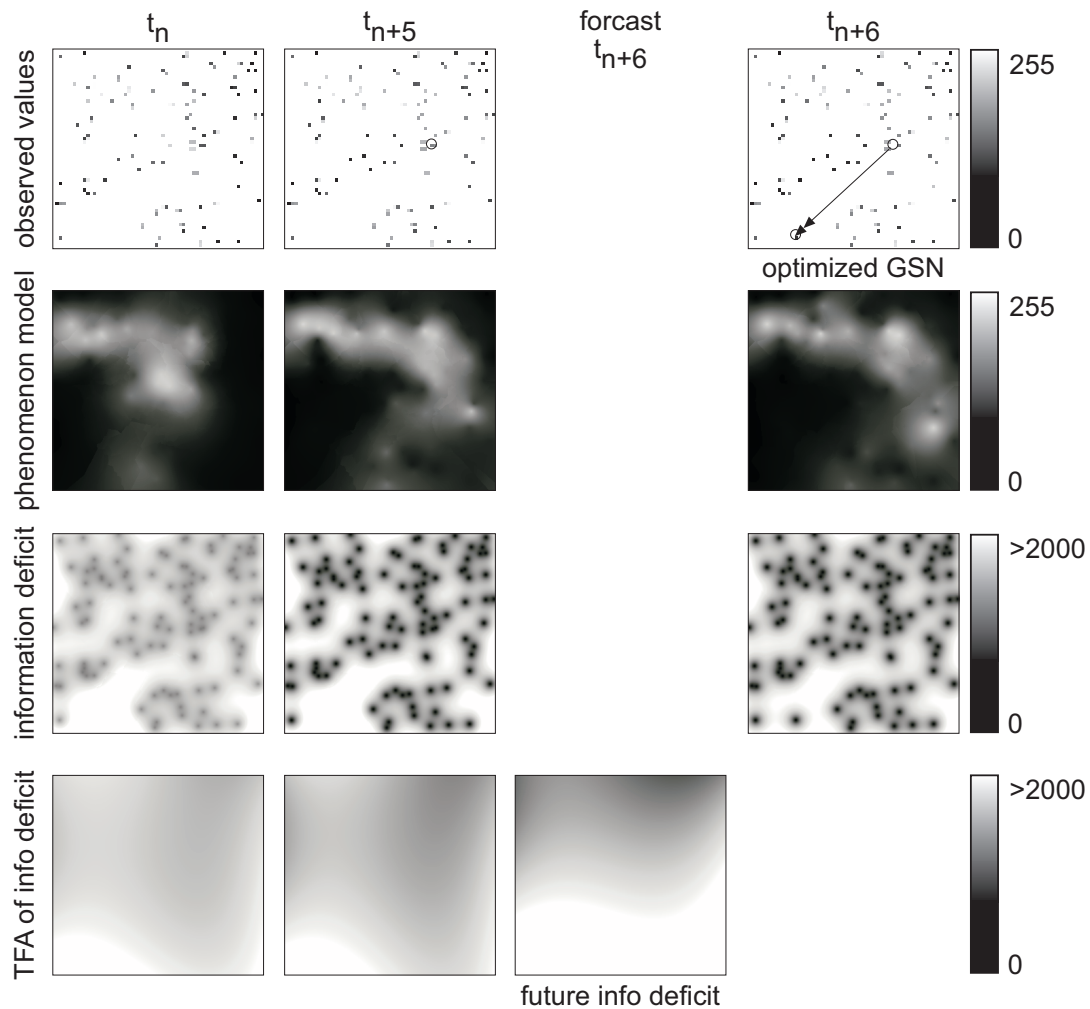


Figure 3: Exemplary results of the first test. The legend of the first two rows refers to the observed ink concentration and in the last two rows to the calculated kriging variance

The example shows, that the model based GSN optimization yields in a more efficient observation scheme. The geosensor nodes are relocated in order to observe the phenomenon at locations where information is needed. The reduced information deficit in Figure 3 (fourth cell of the third row) shows that the geosensor nodes are used more efficiently after the optimization of the network constellation.

5 CONCLUSION

The model-based approach to GSN optimization presented in this paper allows the explicit integration of phenomenon characteristics and geosensor network properties in order to reach an optimal solution. It relies on the minimization of the kriging variance which is used as a measure for the lack of information. By modeling the properties of geosensor nodes using

time geography it is made possible to consider the limitations of geosensor nodes during the optimization process.

The work presented is at an early stage. Future research will have to deal with the following steps:

- Implementation of the GSN model. For the evaluation presented in the previous section only the phenomenon model was implemented into a software module. The GSN model was realized manually.
- Practical evaluation in a real scenario. At the moment the phenomenon was simulated by means of a table top experiment. As a next step an evaluation based on real measurements of a mobile GSN is planned.
- Comparison of the phenomenon model with the real phenomenon. In order to evaluate the usefulness of the kriging variance as single indicator for information deficit, the real phenomenon and the interpolated phenomenon model should be compared.
- Comparison of the model based approach with conventional approaches. Such a comparison will show, if the effort of the presented approach can be justified.

Nevertheless, the presented work shows that the monitoring process of spatiotemporal phenomena could be optimized by means of a model-based approach that combines a phenomenon model with a GSN model.

6 REFERENCES

- Akyildiz I. F., Su W., Sankarasubramaniam Y. and Cayirci E. (2002) Wireless sensor networks: a survey. *Computer Networks* 38:393-422
- Box G. E. P., Jenkins G. M. and Reinsel G. (1994) *Time Series Analysis - forecasting and control*. Upper Saddle River
- Cressie N. A. C. (1993) *Statistics for spatial data*. New York
- Hägerstrand T. (1970) What About People in Regional Science? *Papers of the regional science association* 24:6-21
- Iyengar S. S., Tandon A., Wu Q., Cho E., Rao N. S. V. and Vaishnavi V. K. (2004) Deployment of Sensors: An Overview. In: Iyengar S. S. and Brooks R. R. (eds) *Distributed Sensor Networks*. Boca Raton, pp 483-504
- Karl H. and Willig A. (2005) *Protocols and architectures for wireless sensor networks*. Chichester

- Nittel S. and Stefanidis A. (2005) GeoSensor Networks and Virtual Geo-Reality. In: Stefanidis A. and Nittle S. (eds) GeoSensor Networks. Boca Raton, pp 1-9
- Römer K. and Mattern F. (2004) The Design Space of Wireless Sensor Networks. IEEE Wireless Communications 11:54-61
- Warneke B. (2006) Miniaturizing Sensor Networks with MEMS. In: Mahgoub I. and Ilyas M. (eds) Smart Dust: sensor network applications, architecture, and design. Boca Raton, pp 1-19