Geosensor Networks – chances and challenges

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1 Overview

Sensors are well known in Geodetic Science; also, integrating sensor to sensor networks is not new. This has been done to observe geodetic networks for exact point densification ever since. Traditional geodetic networks consist of a fixed set of dedicated sensors with a given configuration and measurement regime. The processing of the data is usually done in a centralized fashion. Geosensor networks for the observation and monitoring of environmental phenomena are a recent trend in GIScience. What is new is the fact that different sensors act independently, have the capability to communicate and thus the network is able to operate beyond the individual sensors' capabilities. In this way, the network as such is more than the sum of the individual sensors. Besides their own position, geosensors capture information about the environment, such as temperature or humidity. In the context of engineering geodesy, sensor networks are used for monitoring purposes, e.g. to observe and monitor georisks like hang slides. For the future, a miniaturization of the sensors is envisaged, which eventually leads to so-called smart dust, i.e. sensors virtually integrated in the environment. This indicates that the number of sensors is typically very high.

For scalability of the sensor network potentially consisting of a huge amount of sensors, which are distributed in the environmen, different characteristics are essential: wireless communication, ad hoc determination of network topology, i.e. the neighborhood relationships between sensors, as well as local analysis. Thus, there is no central service in the sense of a global data and processing server, which receives and analyzes all the data. Instead, data is processed or at least pre-processed locally on the sensor, typically including information of neighboring sensors. Often, local information only matters locally and thus there is no need for creating a lot of data traffic in the network. In this way, a tight coupling of processing and sensing will be achieved. In summary, geosensor networks are characterized both by distributed data capture and distributed data processing.

Decentralized algorithms for geosensor networks have been investigated by several researchers and for different applications. Laube, Duckham & Wolle (2008) describe an algorithm to detect a moving point pattern, namely a so-called flock pattern. A flock is described as a group of objects that moves in a certain distance over a certain time. In a similar spirit, Laube & Duckham (2009) present a method for the detection of clusters in a decentralized way. Depending on the communication range, clusters of a certain size (radius) can be detected.

There are many applications for Geosensor networks, see, e.g. Stefanidis & Nittel (2005):

- Environmental monitoring
- Disaster management, early warning systems (Bill et al., 2008), e.g. earthquakes, hill slides, …
- Surveillance, risk management (buildings, technical devices, …)
- Military

- Traffic management and monitoring (car2car-communication)
- Topographic Mapping
- Glacier movements
- Human body

Geosensor networks in the sense described above are still in their infancy; today's networks mainly consist of a small number of sensors, often linked by wire; the processing often is done on a central server. However, one can observe an increasing availability of positioning sensors, equipped with additional sensing capabilities, e.g. smartphones. These sensors are already used for massive data collection for the determination of the traffic situation by companies like TomTom or Google. Another example is the exploitation of photos in the web to create 3D-models of landmark objects (Agarwal et al, 2011). This indicates the huge potential, as even low quality sensors, or sensors originally dedicated for other tasks, can yield quality and instant information when integrated in an ad-hoc fashion. With the increasing availability of sensors also their integration and cooperation in terms of sensor networks will evolve.

2 Distributed Processing

In the following, two examples from research at the Institute of Cartography and Geoinformatics at Leibniz Universität Hannover, Germany, are given in order to illustrate the potential and application areas of geosensor networks in an exemplary fashion.

2.1 Using cars as moving rain sensors

One example for the distributed data acquisition is currently being investigated in the context of a project funded by the German Research Foundation, entitled RainCars. Starting point is the fact that exact measurements of rainfall is needed for hydrological planning and water resources management, especially for highly dynamic and nonlinear processes like floods, erosion or wash out of pollutants. Surprisingly, such data is not readily available: there are recording rain gauges, but even in Germany, their spacing is rather poor (one station per 1800 km^2). Rain radar is available at a high temporal resolution and at a spatial resolution of typically 1km*1km. However, radar only measures reflectivity, which has to be transformed to rainfall measurements in a calibration process. Thus the idea of RainCars is to exploit the massive availability of cars and use them as rainfall measurement devices: if it rains, the wiper is put on; depending on the degree of rainfall, the frequency of the wipers is increased.

In this way the cars form a dynamic sensor network. In order to transform the raw measurements (Wiper (W) frequencies) into rainfall (R) values, a functional relationship (WR-relationship) has to be determined. This relationship will be depending on the car type, the inclination of the windshield, but also on other factors like the driver, the location (under tree, in free space), just to name a few. Thus, the idea is to determine the WR-relationship in an iterative and integrated fashion in a sensor network, consisting of the cars and stationary recording rain gauges: As soon as a car comes into the vicinity of a station or another car, it is able to incrementally adapt and correct its current WR-relationship (see Figure 1). The Figure visualizes qualitatively, how the quality of the WR-relationship is increasing, when a car exchanges information with a station, or another car.

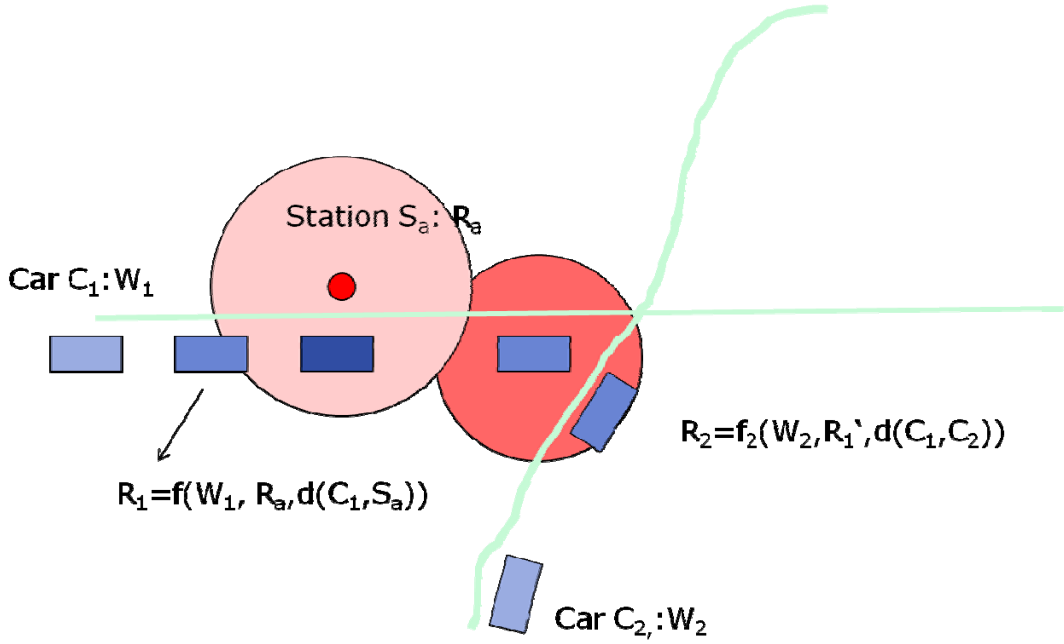

Figure 1: principle of cooperative adaptation of W-R-relationships

In a preliminary simulation study it could been shown that the accuracies achievable using an assumed equipment rate of 4% of all the cars the rainfall estimates determined with the cars moving car network outperform the values determined using traditional methods (Haberlandt & Sester 2010). Figure 2 shows the standard deviation of the rainfall measured in a catchment area using the sensor network. It is clearly visible that in the vicinity of the stations the quality of the rainfall measurements is very high and that this quality is propagated along the most frequently used roads (Schulze et al., 2010).

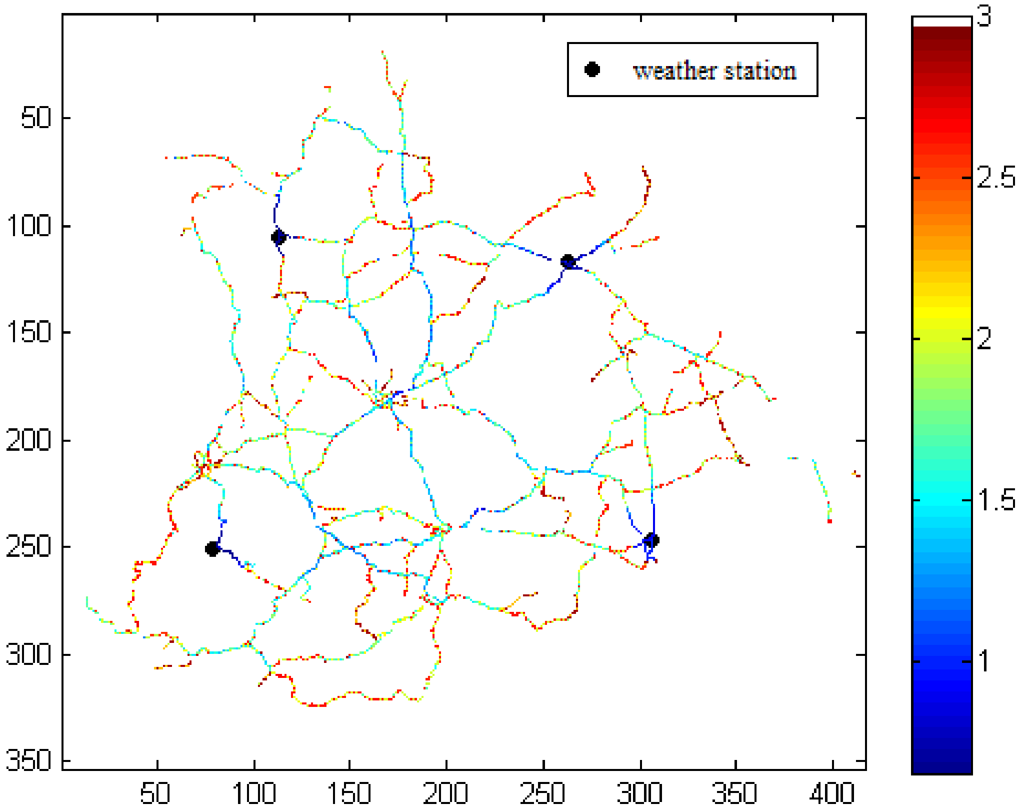

Figure 2: Quality of rainfall measurement.

2.2 Distributed delineation of boundaries of spatial phenomena

Distributed processing can also be used for the scenario that moving sensors have the task to delineate the boundary of a spatial phenomenon, such as an oil spill or the moving area of hill slide. To this end, a distributed algorithm has been proposed, which is able to iteratively approximate the boundary of the phenomenon (Sester, 2009). The algorithm uses the concept of Kohonen Feature Maps (Kohonen, 1982): sensors communicate in their local environment and try to find the boundary of the phenomenon by individually checking pairs of adjacent sensors. A boundary is identified, if both sensors measure different values, i.e. one sensor measures the existence of the phenomenon, the other sensor does not. In this case, the boundary is somewhere between the two sensors. To better delineate the boundary, the sensors move towards each other; in order to better *sample* the boundary, at the same time, these two sensors also drag the sensors in their local neighborhood into that direction, thus leading to the fact that more sensors aggregate on both sides of the boundary. This principle is shown in the following Figure 3: sensors A and B detect the boundary in between them; they move towards each other, dragging their neighbors with them.

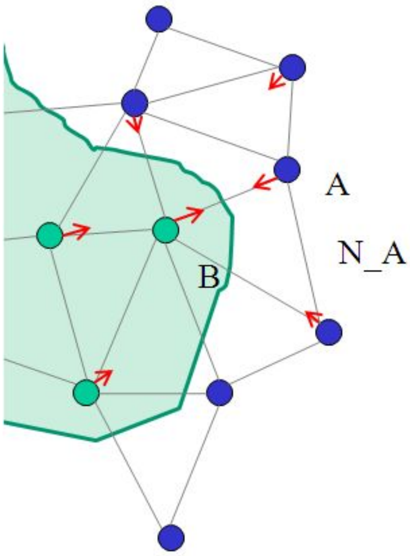

Figure 3: Principle of iterative adaptation of sensors (circles) to phenomenon (polygon)

Figure 4 shows an application where a set of sensors has to detect a concave phenomenon. The sensors are spread out in a random fashion. On the left is the initial situation of the spatial phenomenon in light blue, whose boundary has to be approximated; the point sensors are randomly distributed in the beginning and they are measuring the phenomenon (blue) or not (red). If they are exactly on the boundary, they are shown in yellow. The figure in the middle shows the movements of the sensors during the iterative adjustment, and the situation on the right shows the situation after the adaptation. It clearly indicates that the boundary is nicely approximated by many sensors. Some sensors are still in the middle of the phenomenon – this is due to the fact that they were not in the communication range of neighboring sensors and thus were not dragged towards the boundary.

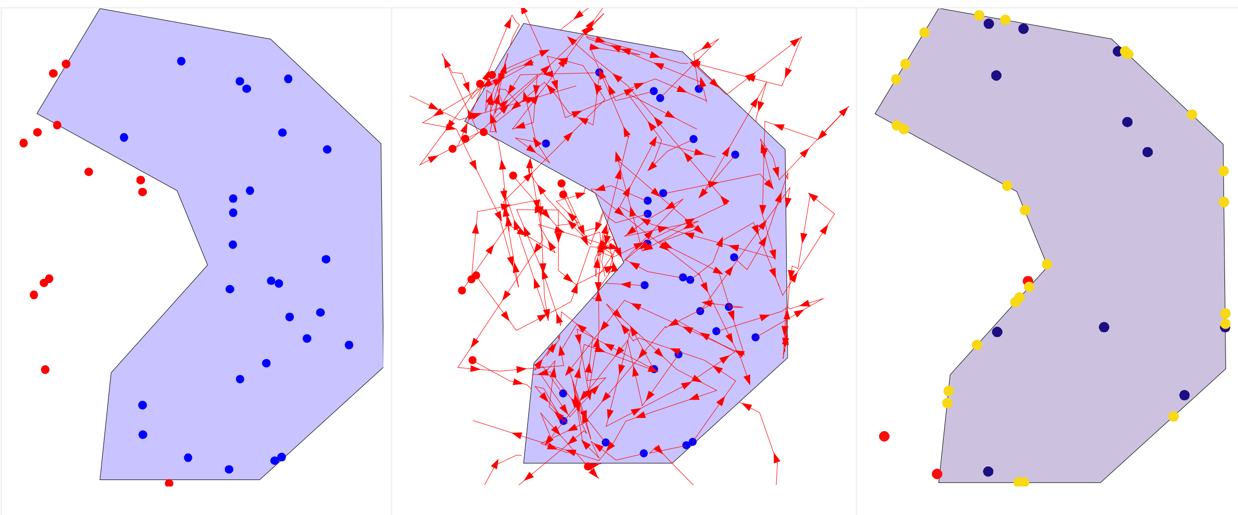

Figure 4: Detection of the boundary of a phenomenon: areal phenomenon and initial sensor distribution (left), movement of neurons (middle) and approximate boundary points in yellow (right).

2.3 New Maps

In the context of sensor networks and the massive availability of environmental data, a new, dynamic understanding of digital maps for recording these data is needed. The automatic processing of these masses of distributed sensor data demands for adequate representation forms. A future aim is a system, which – depending on the given task – assembles, analyzes and interprets the given data and thus derives higher level constructs from it (Brenner, 2006). In this way, a self adapting map is created, which knows its quality and its application ranges.

This also includes the fact that the maps of the future might not only be readable by humans, but also contain elements that make them readily usable by machines. Thus the map features have to be close to the interpretation capabilities of the machine. Only then an immediate and exact identification of the correspondence of map features and features recognized in the environment is possible for the machine. This principle is being applied in robotics, where often so called occupancy grids are used to determine areas, where an autonomous system is able to move around. Brenner (2009) extends this concept by introducing higher level features than just pixels. These features, vertical poles, are distinct features in a road environment and can easily be extracted with automatic processes from Lidar data (see Figure 5).

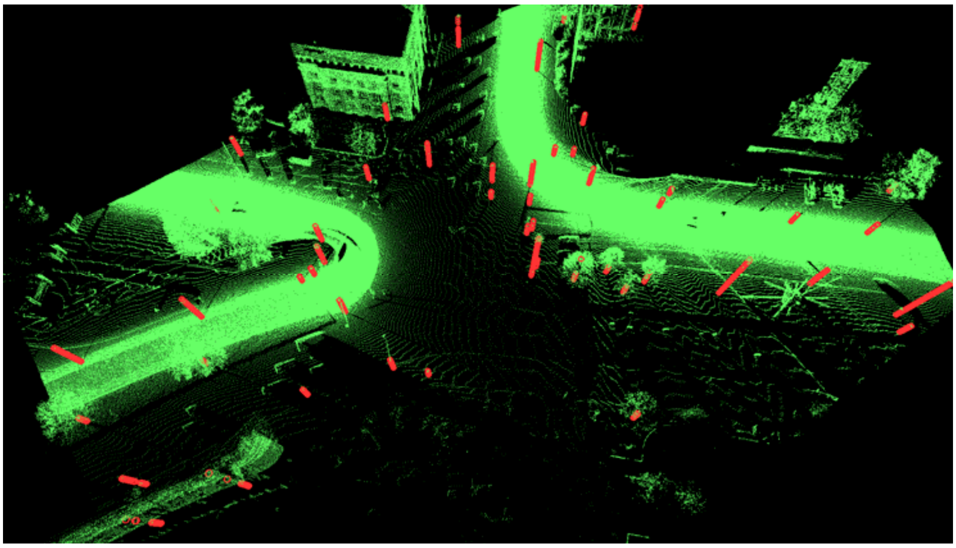

Figure 5: Automatically extracted poles (vertical structures) from a Lidar Point cloud (Brenner, 2009).

These features can be used for exact positioning of a vehicle in the environment. Figure 6 shows a map with the achievable accuracies using the poles as ground-control features: the distribution and density of the poles directly influences the quality (Hofmann et al., 2011). Along highways, there are typically no poles, thus, no position can be determined using this method. However, in city areas, accuracies in the low dm-range can be achieved. Thus, such a system can ideally complement GPS, which has problems in dense city areas and performs well in highway areas with free sky view.

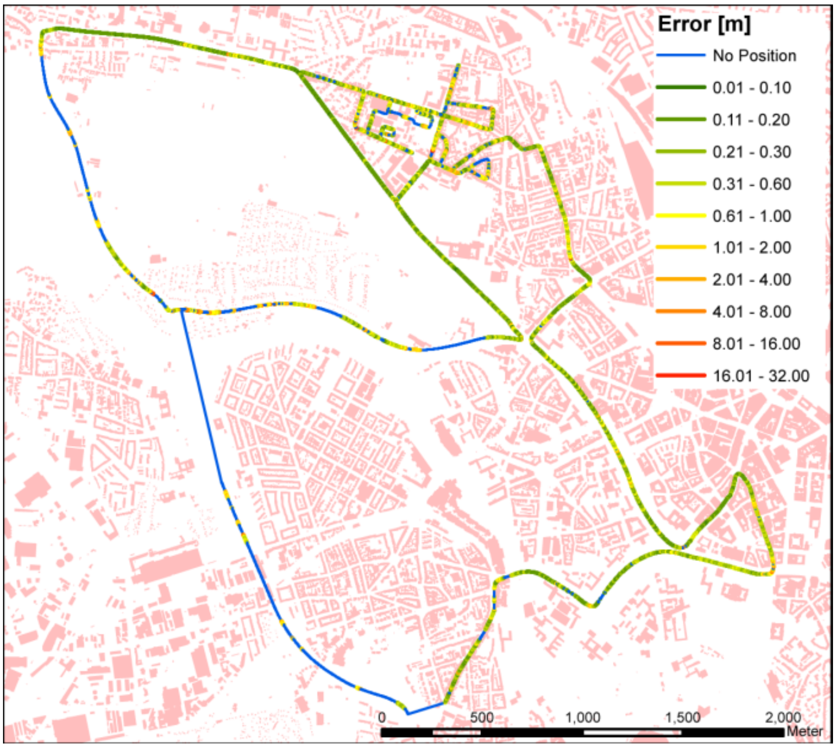

Figure 6: Achievable accuracies using vertical poles as positioning references.

3 Consequences for future mapping and maps

The ever increasing number of sensors leads to a situation where we have a lot of measurements, even related to the same spatial situation. The data will be heterogeneous, of different quality, temporal and spatial resolution, different scale, inhomogeneous spatial coverage and of different type, ranging from low-level information to high-level data, such as raw Lidar points to GIS-data. There are several benefits of such a situation, e.g. data can be incrementally refined and enriched using sensors with complementary capabilities. Also, repetitive measurements can lead to an increase in accuracy of the data and an immediate quality check. Having many sensors available leads to redundancy and thus to fault tolerance, as the system does not depend on one sensor alone. Also, scalability can be achieved. The information is directly available, as soon as it is acquired, and can be used in an instant fashion. Using the concept of a dynamic map, which is able to adapt its contents to the applications, leads to a high degree of data reuse.

There are new challenges which pose new demands on mapping, which can only be met with new sensors and sensor integration: already now, but even more so in the near future, we will have ***new users***, but also ***new applications*** which demand for high resolution environmental data, in geometric, temporal and thematic dimension, and in different abstraction hierarchies.

More and more, we see different users of the maps: whereas previously, map usage was mainly targeted at humans, nowadays also automatic or assisted systems are relying on accurate and adequate maps. ***New applications*** – both on the low end side in terms of Apps for Smartphones, but also on the high end side in assisted system, are coming to the market. For a navigation system to operate satisfactory the geometric accuracy has to be in the dm-range in order to allow for precise driving directions, also the timeliness has to be very high. An autonomous robot has to have sensors to capture the current local situation and map it to the knowledge encoded in the map. To this end, the dynamics of the environment has to be integrated in the map, on order to allow the system to interpret and explain the sensed features has available.

Geosensor networks have the potential to serve these needs. Besides the developments in sensor technology, also new methods for data processing have to be developed, as well as new data structures to adequately manage the data. Besides storing the mere information, also information about its quality has to be captured and processed. Also, methods and processes to handle and respect privacy have to be developed.

4 References

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