An Experiment on Geosensor Mobility Strategies in the Planar Space

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SUMMARY

At present, research on mobile geosensor networks gains more and more attention in the geographic information science. Such networks may be deployed to monitor and capture the spatio-temporal variance of phenomena appearing in the geographic space. Each node in a network is either self-propelled or carried in space by agents. In this paper we take a closer look at three exemplary mobility strategies for self-propelled geosensors. We hypothesize that the ability of individual geosensors to adapt their mobility to stimuli in the physical world improves the model of the phenomenon being captured by a mobile geosensor network over a finite time period. An executable model provides empirical evidence for our assumption. However, the scientific inquiry and the resulting findings are at an early stage. There is a need to cope with more complex models to come around with grounded theories. Before we conclude our work, we formulate four directions for continuing the research presented herein.

KEYWORDS: *mobile geosensor network, spatio-temporal modeling, real-time data acquisition*

INTRODUCTION

Academic research on geosensor networks has been recently popularized by a number of workshops and conferences in the field of geographic information science, e.g. the First Workshop on Geo Sensor Networks in 2003 (Nittel, Stefanidis et al., 2004) or the Workshop on Interoperable Sensor-Networks held in Göttingen (Germany) in 2004 (Simonis, 2004). The application possibilities of such networks are manifold. For instance, climatologic measurements may be conducted by means of a stationary network (geosensors being attached to weather stations) or a mobile network (geosensors being deployed inside monitoring vehicles). This paper puts its primary scope on the latter network type.

In general terms, a mobile geosensor network comprises of a large number of unattended and untethered sensors that move autonomously or are carried by agents in geographic space, and which collectively monitor objects and occurrences (referred here to as phenomena) appearing therein. Once deployed in physical space, each geosensor associates the phenomenon it senses with the geographic location it populates, and disseminates the respective data.

Such geographically dispersed networks are characterized by multiple concurrently executing processes (e.g. monitoring, mobility, communication), which take place in response to stimuli in the physical world (e.g. spatio-temporal variance of sensed phenomena, proximity to other geosensors, data requests). Thus, mobile geosensor networks can be said to constitute reactive, or in other words, event-driven distributed systems. However, while research on monitoring and communication (e.g. Nittel, Duckham et al., 2004) in mobile geosensor networks has been recently started, work on geosensor mobility strategies remains rare in the geographic information science today.

In this work, we hypothesize that the ability of individual geosensors to adapt their mobility to stimuli in the physical world improves the model of the spatio-temporal phenomenon being captured by a mobile geosensor network over a finite time period. We particularly study the impact of three basic mobility strategies on the resulting model of the phenomenon being monitored by a finite set of geosensors. The detection rate (the captured extent of the phenomenon in relation to the total extent of the phenomenon) constitutes the effectiveness measure for each mobility strategy in this work. Based on simulation results we assess how the number of mobile geosensors, the actual mobility strategy, and the structure and dynamics of a phenomenon influence the completeness of a phenomenon's representation over a fixed number of discrete time periods.

The paper in hand is organized as follows. Based on an application example, chapter two establishes the necessary background on mobile geosensor networks and their properties in contrast to stationary geosensor networks. In chapter three, we introduce the reader into our experiment that aims at delivering an empirical evidence for the effectiveness of three different mobility strategies. Thereby, we concretize our hypothesis, set up the working assumptions, present the underlying scenario, and formulate the geosensor mobility strategies, i.e. random mobility, autonomous mobility, cooperative mobility. The presentation of the simulation results is the matter of chapter four. In chapter five, we analyze the results in comparison with the performance of a stationary geosensor network. In the sixth chapter we discuss the findings and draw also upon the implications as well as the benefits and limitations of the approach taken herein. The paper terminates with chapters seven and eight presenting future research prospects and concluding the work, respectively.

ON MOBILE GEOSENSOR NETWORKS

Geosensor networks are deployed to monitor and capture the spatio-temporal variance of phenomena appearing in the geographic space. For example, Szewczyk, Osterweil et al. (2004) deal with the utilization of in-situ geosensors for habitat monitoring. In earlier days, models of the microclimate at certain localities under scope were extrapolated from past measurements of few sites. Nowadays, a spatially dispersed stationary geosensor network is capable of capturing the full exposure of a phenomenon taking place in a habitat patch. Thereby, each node in the geosensor network continuously measures (possibly in different frequencies) one observable or a heterogeneous set of observables at the location it resides. Dependent on the geosensor hardware capability the observables may comprise of sunlight, temperature, humidity, air pressure, precipitation, or wind speed at ground, to name just the climatologic ones. The resulting fine-grained data in terms of their spatial and temporal resolution enable the environmental scientist to obtain unprecedented models and predictions of environmental processes.

A reliable representation of a microclimate requires a dense distribution of stationary geosensors interior of the relevant fraction of geographic space. However, unforeseen battery depletions or technical failures may make geosensors collapse before the scheduled time for monitoring has elapsed. In such a case, the environmental scientist has to cope with increases in uncertainty in the spatial distribution of the investigated phenomenon resulting from gaps in the geosensor network. To the same degree, seasonality, anomalies or disturbance events may cause the microclimate phenomenon to expose a spatial pattern that does not overlap with the area currently monitored by existing geosensors. The immobility of such geosensors prevents the entire network to adapt the distribution of its nodes with the dynamics of the phenomenon under scope. These limitations establish the rationale to deploy mobile geosensor networks.

We view the mobile counterpart of a stationary geosensor network as a network consisting of self-propelled geosensors or geosensors that are carried in space by robot or animal agents. The mobility of every geosensor is assumed to be governed by an array of possible constraints. In this paper we do not intend to embark on discussions regarding the geosensor capability to proceed between two distinct locations; bearing also in mind the likely impact of the topography on the geosensor's mobility. Rather, we address the question of how geosensors decide what path to take through the physical space in response to external stimuli, most notably in response to the dynamics of a monitored phenomenon.

Let us for a moment assume a mobile geosensor network that is deployed to conduct habitat monitoring. All geosensors in that network are thereby equipped with a uniform movement strategy that allows them to proceed from one location to another. If a geosensor is carried by an autonomous agent (mammal or insect) the possibilities to follow a movement strategy and dictate the respective path may be limited. But if a geosensor is either self-propelled or attached to an artificial agent, it can exhibit mobility that is determined by its underlying movement strategy and external stimuli. We assume that already very simple mobility rules (e.g. keep location as long as the phenomenon persists at that location, otherwise proceed to another location within the discrete monitoring area) can improve the model of the phenomenon being captured by the entire geosensor network. With this assumption we continue on the work done, for instance, in robotics. The following sections will provide empirical evidences that support our position.

THE EXPERIMENT SETTINGS

We contend that once fully investigated, mobile geosensor networks will establish a valuable means for the monitoring of the structural and positional exposure of phenomena in geographic space. (The thematic variability of the phenomena is not covered in this work). However, the effectiveness of such networks may in practical settings be dependent upon the path every geosensor follows through space and time, which, to a huge extent, is determined by the underlying mobility strategy. Effectiveness refers here to the captured extent of the phenomenon in relation to the total extent of the phenomenon (i.e. the detection rate).

In this context, we suggest a conjecture to acquire this missing knowledge. It comprises the formulation of a theoretical proposition by means of a hypothesis. The hypothesis shall establish an anticipated conclusion about the relationship between the variables from the research context. Thus, we hypothesize that a geosensor mobility strategy provides a detailed model (expressed in terms of the detection rate) of the spatio-temporal phenomenon being captured by a mobile geosensor network over a finite time period only if it responds to the stimuli in the physical world.

For the testing of our hypothesis we construct a planar space where discrete phenomena take place and exhibit certain spatio-temporal dynamics. For simplicity reasons, we choose a field-based representation of homogenous space with a fixed extent of 10x10 equally sized quadratic fields. The discrete phenomena comprise of three different types, i.e. moving phenomenon, expanding phenomenon, and contracting phenomenon. They appear in the initial state of the model in t_1 and alter their structure and location during seven transitions until the final state is reached in t_8. Thus, we partition time into eight discrete periods where $T = \{t_1, t_2, t_3, ..., t_8\}$.

The moving phenomenon occupies a quadratic area of nine connected fields. It retains its structure as it proceeds from the upper left corner of the planar space to the lower right corner (see figure 1a). At each iteration, the phenomenon moves where the index *(m, n)* of its fields changes to *(m+1, n+1)*. The expanding and contracting phenomena are characterized by changes in structure and location alike. In t_1 the former phenomenon type occupies one field with the index *(1, 1)* and grows in size as time elapses. With each iteration the phenomenon's proximate fields *(m+1, n)* and *(m, n+1)* become part of it. In t_8 this phenomenon consists of 36 connected fields and possesses a triangular structure (see figure 1b). The contracting phenomenon exposes contrariwise dynamics. In t_1 its initial structure equals the structure of the expanding phenomenon in t_8. It decreases in size as time elapses. In t_8 this phenomenon occupies one field in the very upper left corner of the planar space (see figure 1c).

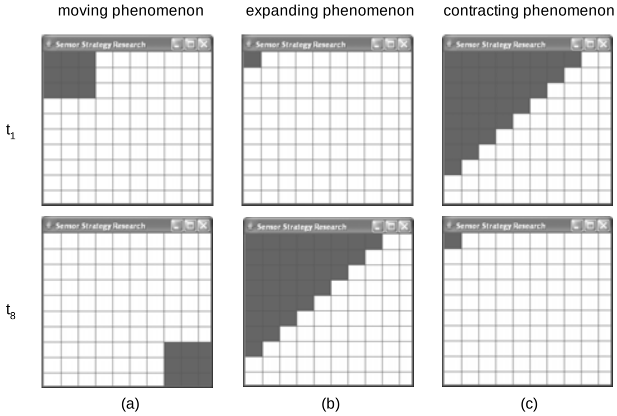

Figure 1: Spatio-temporal phenomena in scope

In t_1 a mobile geosensor network is deployed in the planar space where the size n of the network is $0 < n \leq 50$. In this initial state the geosensors are randomly dispersed but none field may be occupied by two or more geosensors. As time elapses from t_i to t_{i+1}, a geosensor either retains its source field or it proceeds to occupy another field in the Moore neighborhood. Dependent on the geosensor's location within the planar space (e.g. inner part, fringe, or corner) the number of possible target fields may be eight, five or three (see figure 2). However, the underlying strategy and external stimuli determine the actual movement direction of a geosensor.

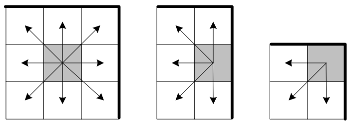

Figure 2: Moore neighborhood

In our experiment the geosensors are equipped with one of the three possible mobility strategies. The *random mobility strategy* makes geosensors move randomly in planar space. On each iteration all geosensors proceed to another field. This implies that the source location in t_i cannot become the target location in t_{i+1}. Except in t_1, one or more geosensors may share a location at the same time.

Using the *autonomous mobility strategy* the geosensors also move randomly in planar space as prescribed by the random mobility strategy. However, if a geosensor detects the exposure of a phenomenon at its current location, the geosensor remains there as long as the phenomenon persists in that field. Once the phenomenon vanishes from that field, the geosensor continues its random movement.

The *cooperative mobility strategy* basically extends the rules of the autonomous mobility strategy. An additional constraint is that two or more geosensors cannot occupy the same field at the same time. This implies that all geosensors are aware of the presence of their peers. Thereby, a geosensor proceeds to another location only if no other geosensor is present in the target field. If the entire Moore neighborhood is populated with geosensors, it keeps the source field until at least one field in the neighborhood does not accommodate any other geosensor. The target field is then randomly determined. If a geosensor measures the exposure of a phenomenon at a given location, it remains there as long as the phenomenon persists. Once the phenomenon vanishes from the location being occupied by the geosensor and at least one field is unoccupied within its Moore neighborhood, the sensor continues its random movement. Otherwise the geosensor keeps its location.

The model presented in this chapter has been implemented using the Java programming language. A critical issue concerns the generation of pseudorandom values to let geosensors move randomly through the planar space. We have chosen *Mersenne Twister* and define the seed as the current CPU system time in nanoseconds (Matsumoto & Nishimura, 1999). The full source code of our model is available from the incubator area of the open source software initiative 52°North[1].

SIMULATION RESULTS

For different numbers of geosensors 100 model runs were executed to look how different mobility strategies influence the detection rate of the three aforementioned phenomena. Exemplary tests with 1000 runs had proven that the results differ only marginally. To provide a better understanding of the experiment, figure 3 depicts the results of a chosen simulation run. Both illustrations in 3a and 3b show the dynamics of the moving phenomenon in the first row, and the distribution of 25 sensors within the 10x10 fields planar space in the second. The third row reports the fields being detected by the geosensors, which is remarkably higher in figure 3b compared to 3a. Figure 3a shows randomly moving geosensors, whereas the geosensors in figure 3b follow the cooperative mobility strategy. The autonomous mobility strategy had been omitted in this illustration for clarity.

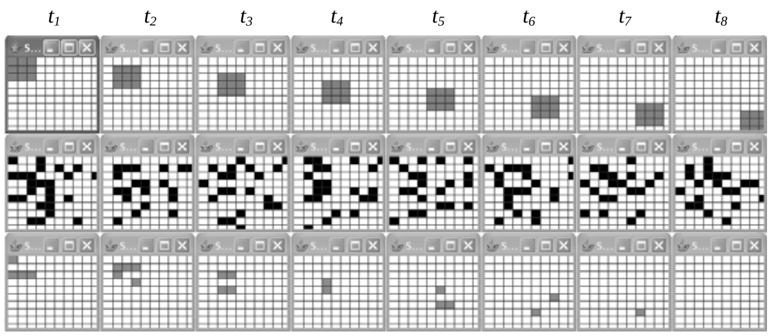

Figure 3a: Experimental results with 25 sensors, following the random mobility strategy

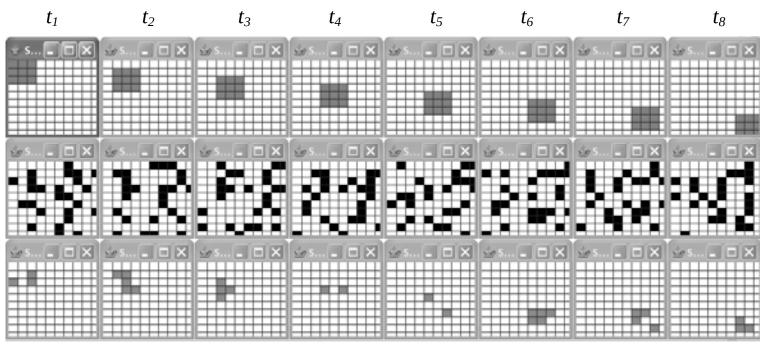

Figure 3b: Experimental results with 25 sensors, following the cooperative mobility strategy

[1] See http://www.52north.org

The figures 4 to 6 show the detection rate in percent for each phenomenon. The three curves mirror the effectiveness of the three different strategies the geosensors in the network may be using. The dotted line illustrates the detection rate for the randomly moving geosensors. From five geosensors onwards, the detection rate is clearly lower than the one for the other two strategies. The autonomous and the cooperative mobility strategy differ in a considerable manner from 15 sensors onwards. Differences of the lines at one geosensor are purely by chance.

The results for the expanding phenomenon show similar details like the ones for the contracting phenomenon. If more than two geosensors are deployed, the detection rates achieved by geosensors that use the autonomous and cooperative mobility strategy exceed the respective values of the randomly moving sensors. Interestingly, the results for the two more sophisticated strategies differ remarkably only from 20 geosensors onwards, having a similar rate for 35 geosensors. The difference at the one geosensor level is purely by chance again.

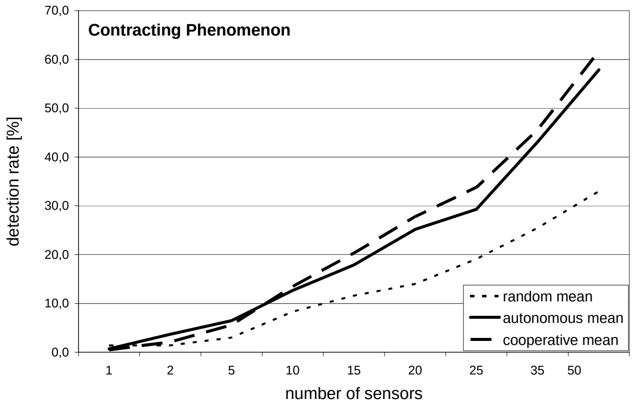

Figure 4: Detection rate for different numbers of geosensors; contracting phenomenon

The detection rate for geosensor networks monitoring the expanding phenomenon is lower compared it with the contracting phenomenon, except for the randomly moving geosensors. This is valid for the autonomous and the cooperative mobility strategy due to the fact that the overall number of fields the phenomenon occupies in t_1 is higher, where many geosensors are likely to keep the initial location. The latter might be an experimental artifact. Because the overall number of phenomenon fields is the same for both phenomenon types during all time periods (the expanding phenomenon starts at a single field and ends with 36 occupied fields after eight time periods, whereas the contracting phenomenon shrinks contrariwise), it could be presumed that the two values will converge as the number of runs grows.

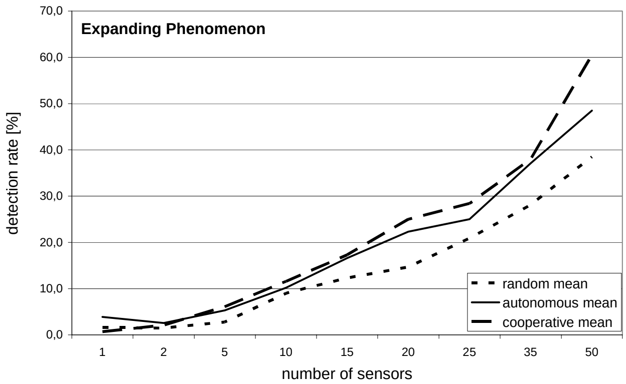

Figure 5: Detection rate for different numbers of geosensors; expanding phenomenon

We observe the most distinct results for the moving phenomenon. Here, the three curves show a clear improvement of the detection rate. The values at the one geosensor level are almost identical. Starting from ten geosensors onwards, the cooperative mobility strategy increasingly outperforms the autonomous mobility strategy.

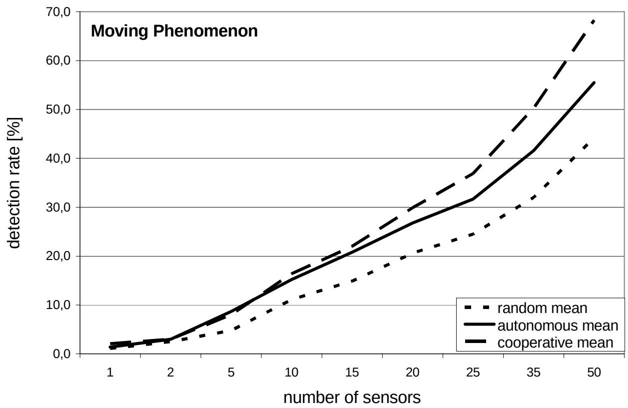

Figure 6: Detection rate for different numbers of geosensors; moving phenomenon

ANALYSIS

In more detail, we investigated the statistical sample of the detection rates at the network size of 25 geosensors for the three different phenomena types and the three different mobility strategies. In order to provide a reference, we also contrasted the results of the mobile geosensor networks against the results obtained by means of a stationary network. The stationary geosensors were also distributed in space by random. They populated the planar space in the way that only one sensor occupied a discrete field. The general observation is that mobile geosensors outperform the stationary ones in terms of the mean detection rate if they apply the autonomous or the cooperative mobility strategy (see figure 7).

Mean Detection Rates for 25 Geosensors

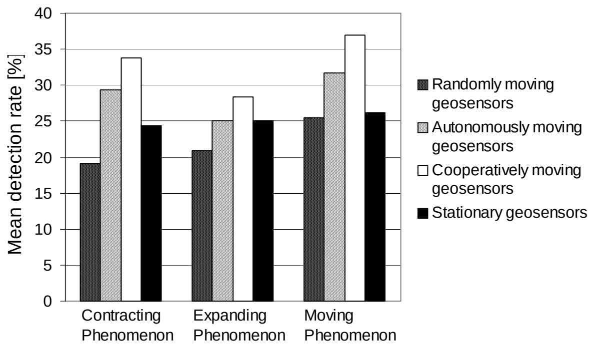

Figure 7: Mean detection rates

Using the random mobility strategy the 25 mobile geosensors detected at the minimum 2.6%, at the maximum 44.8%, and in average 19.1% of the contracting phenomenon's exposure (median was 18.2%). The autonomous geosensors detected at the minimum 5.3%, at the maximum 64.0%, and in average 29.3% (median was 26.3%); the cooperative geosensors reported percentage values amounting at 6.8%, 64.4%, and 33.8% (median almost equaled the average value), respectively. As a reference, the stationary geosensor network achieved detection rates that amounted in minimum at 3.7% and in maximum at 70%. The mean value was 24.3%.

The results for the randomly moving geosensors that monitor the expanding phenomenon are very close to the results of the contracting phenomenon. The minimum detection rate was 2.4%, the maximum rate amounted at 43.0%, and the mean reached 20.9% (median is 18.2%). The autonomously moving geosensors detected at the minimum 2.8%, at the maximum 65.1%, and in average 25.0% of the phenomenon's exposure. If outliers are not taken into account, the maximum value exceeded slightly 51%. For the cooperatively moving geosensors the detection rates amounted at 4.5%, 58.8%, and 28.4%, respectively (median is 27.1%). The maximum value of the cooperative mobility strategy was rather low compared to the autonomous value of 65.1%, whereas the average value was 3.4 points higher. Compared to all other phenomena, the results were very much scattered. In contrast, the stationary geosensor network reported the following values: minimum was 4.5%, maximum was 58.1%, and the mean amounted at 25.1%.

The sample for the moving phenomenon monitored by mobile geosensors is characterized by the lowest range. The minimum detection rate of the randomly moving geosensors was 9.7%, the maximum rate reached 38.9%. The mean detection rate amounted at 25.5%. If we remove outliers from the sample, the minimum rate amounted at almost 13.9%; the maximum rate dropped down to 37.5%. The autonomous mobility strategy showed distinct improvements with 19.4%, 48.6% (or 44.4%, if outliers were removed), and 31.7% as the mean value for the total sample, respectively. The cooperatively moving geosensors achieved detection rates that amounted at 19.4%, 55.6%, and 36.9%, which is a remarkable improvement as far as the average detection rate is concerned. If outliers were removed, minimum detection rate increased to 23.6% and the maximum rate dropped to 48.6%. In comparison, the stationary geosensor network achieved a minimum detection rate of 12.5%, a maximum value of 40.3, and a mean detection rate of 26.1%.

DISCUSSION

In general, the observed data provide support for our hypothesis. However, we have to improve our models as an increase of scientific rigor is always desirable. Much of possible improvements are addressed in the section on future research. In this section we critically elaborate on our experiment settings and the obtained results.

The experiment's results witness a high interrelation between the phenomenon detection rate and the mobility strategy of a geosensor network. Both, for one or two geosensors, the differences between the three strategies, independently of the actual phenomenon in scope, are virtually negligible (bearing in mind the limited number of model runs). Compared with the random mobility strategy, considerable improvements occur if at least 5 geosensors either use the autonomous mobility or the cooperative mobility strategy. Regarding our experiment settings, this means that at the initial state at least 5% of the planar space is occupied by geosensors. The cooperative mobility strategy outperforms the autonomous strategy if 10 or more geosensors are deployed; or in other words if 10% of the planar space is covered with geosensors in t_1.

For the experiment, we use an arbitrary number of geosensors. The range spans from at least one geosensor to fifty such hardware units, covering a maximum of 50% of the entire space in t_1. As far as real world monitoring applications are concerned, we would have to reason about the appropriate number of geosensors for a particular real world monitoring task. In this context, it is interesting to analyze whether or not there is any rationale to decide on a fixed number of mobile geosensors; taking geosensor deployment, maintenance, and failure costs into account.

Our model uses a rather simple approach for the discretization of space and time. The phenomena are capable of moving one field from the source location to a target location in the Moore neighborhood on the transition from t_i to t_{i+1}. Consequently, the model fulfills the Courant-Friedrich-Lévy condition. We suppose that this approach is sufficient to analyze geosensor moving strategies at a very basic level, although we have to represent real world conditions to verify our results.

We did not yet consider disjoint phenomena. This might be a shortcoming of our approach, which has to be addressed in future work. Additionally, we have to investigate the work of the agent based simulation community and evaluate existing multi-agent systems (e.g. SWORM) for their applicability to execute our models.

FUTURE RESEARCH

In this paper we have demonstrated the impact of geosensor mobility strategies on the spatio-temporal model of the phenomenon being captured by a mobile geosensor network. Our scientific inquiry and the resulting findings are, however, at an early stage. There is a need to cope with more complex models to come around with theories. In this context, we identify four research directions.

(1) The geosensor mobility strategies presented in this paper are based on very simple rules. The development and testing of additional such strategies will undoubtedly provide more insight on how the mobility of individual geosensors aids the monitoring of spatio-temporal phenomena of various types. Among several ideas, we assume that the consideration of collaborative features is likely to lead to results that outperform those obtained from our experiment. For instance, allowing geosensors to communicate to each other may be beneficial if networks have to cope with complex, e.g. disjoint moving phenomena.

(2) If geosensors are not aware of locations where the phenomenon's exposure have been reported by other geosensors, they cannot directly migrate to those areas where the phenomenon is likely to take place in the future. Thus, experiments with self-organizing mobile geosensor networks deserve attention. We propose three types of communication in order to allow geosensors exchange information about detections: broadcasting, hub-and-spoke, and peer to peer (i.a. flooding). Once a geosensor has received information from other nodes, it either must possess the capability to predict the future structure and location of the phenomenon and to choose a target location appropriately. Or

a central intelligence unit must have access to all geosensor data and execute such a capability in order to task individual geosensors with appropriate monitoring paths. The development of such a capability (either decentralized or centralized) constitutes a challenging research task.

(3) So far we have focused on mobile geosensor networks where all its nodes use a uniform mobility strategy throughout the monitoring task. In future we will improve our models to observe how a mobile network behaves if its nodes are bundled to form multiple sub-networks, each having a different strategy. Moreover, we will enable single geosensors to switch between different mobility strategies in response to certain external stimuli or emergent patterns of geosensor distribution.

(4) Up to now, our ideas and assumptions on geosensor mobility materialized in simulations where networks were deployed in homogenous planar spaces. We expect that the incorporation of sophisticated monitoring environments will push our models closer toward real world applications. Consequently, we have to proceed from planar to three dimensional spaces where topography matters and has influence on the mobility of geosensors and monitored phenomena alike.

CONCLUSION

In this paper we have investigated the impact of geosensor mobility strategies in mobile geosensor networks on the resulting model of the spatio-temporal phenomena. Already very simple mobility rules matter. Our focus was on enabling geosensors to adapt their behavior to external stimuli and exhibit an individual mobility that caters for the task of the entire network. Our experiment results also indicated that some strategies may outperform others. Up to now little is known about what geosensors should be aware of in order to improve the monitoring of spatially dispersed mobile geosensor networks. But we may benefit from related research in the area of robotics and multi-agent systems. This may open up possibilities for interdisciplinary research on hardware and software systems for those networks described in this work.

ACKNOWLEDGEMENTS

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