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SIC2004: an exercise for automatic mapping in emergencies

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Introduction

Computer-based decision-support systems for nuclear emergencies are, in many respects, similar to systems used to monitor natural hazards. For instance, monitoring networks regularly collect and report local observations of a variable that need to be converted into information with spatial continuity, in other words, maps that might be essential for decision-making. Ideally, these maps should be established automatically in order to allow real-time assessments and to minimize human intervention in case of emergency. Automating the spatial interpolation step is not as straightforward is it may sound: many methods exist, and each has its advantages and disadvantages. The choice of a method depends mainly on:

1. the nature of the data,

2. the density and spatial distribution of the sampling points,

3. the spatial variability of the variable,

4. the initial assumptions made on the phenomena being studied,

5. the goals of the study (description, quantification, identification of hot spots, etc),

6. the desired level of accuracy,

7. the computing load,

8. the experience of the user.

Once a choice is made, one will furthermore have to select a number of parameters from which many are defined arbitrarily. These parameters are usually selected by time-consuming cross-validations, and each test has to be repeated once new data are analysed.

SIC2004

In order to explore further the factors that need to be taken into account when designing decision-support systems which involve automatic interpolation at some stage, an exercise was organised in 2004 by the Radioactivity Environmental Monitoring Group (Institute for Environment and Sustainability, Joint Research Centre, European Commission). The Spatial Interpolation Comparison 2004 (SIC2004; see EUR, 2005) statistical exercise was organised on the internet: participants were invited to design algorithms for automatic mapping on the basis of daily dose-rate measurements reported by the German national automatic monitoring network (IMIS) of the Federal Office for Radiation Protection.

Practically speaking, participants were provided with a set of n daily measurements and asked to estimate values assumed by the variable at a number of $N - n$ locations. The real values observed at these $N - n$ sampling places were revealed only at the end of the exercise in order to assess the relative performances of the proposed algorithms. Another essential consideration for the participants was that the algorithms had to be able to deal with extreme events that would affect the statistical portrait of the monitored phenomenon. This may happen when stations malfunction or if disasters occur and, as a consequence, measured values by far exceed background levels. To explore the response of interpolation algorithms to such extreme events, a second test dataset simulating an accidental release of radioactivity into the atmosphere was also used. A small corner of the monitored area was chosen, and a dispersion process was modelled in order to obtain a few values on the order of 10 times more than the overall background levels reported in the first dataset.

The participants chose mainly two types of functions: geostatistical functions and machine-learning algorithms. Both are statistical techniques and, since a minimum number of observations are required for drawing any kind of portrait of the studied phenomenon, the discussions that will follow cannot be generalised to all systems. This aspect of the problem underlines the need for physical models in early phases of disasters as only very few observations are available to describe the situation.

The robustness of geostatistical methods (see e.g. Chiles and Delfiner, 1999) accounts for the increasing use of these functions in environmental sciences. Nevertheless, their performance depends strongly on the model chosen to describe the spatial correlation of the variable (the semivariogram) which is used to derive the weights of the estima-

tion function. In addition, semivariogram models are frequently difficult to estimate accurately in areas with strong, local fluctuations and/or sparse information. In this regard, semivariogram fitting still remains the weak point of such functions in terms of automatic processing.

Concerning the self-learning ability of machine-learning algorithms (see e.g. Bishop, 1995), they seem to offer an interesting solution by providing the expert with methods that appear to be independent of any a priori knowledge of the spatial correlation of the phenomenon under investigation. However, these methods are still relatively new and need further testing as well as a sound methodology in order to tune the numerous parameters that they require. The main parameters to optimise include the number of hidden layers, interconnecting nodes, tolerance, and so forth.

Results

In the first scenario, that is of routine monitoring, almost all of the 32 algorithms submitted gave very similar results, and the correlation between estimated and true values were good in almost all cases (Pearson's correlation coefficient ranged between 0.70 and 0.80). This is not a surprise as participants had a few months to design their algorithms, and the data used for training were very similar to those used for the exercise. A few outliers in terms of performance were nevertheless noticeable as the correlation was clearly below or close to 0.50. These outliers were produced by machine-learning algorithms. A similar observation could be made in a previous exercise (SIC97, EUR 2003): geostatistical functions confirmed their reputation for robustness, and, independently of the model chosen for spatial correlation, they all generated good results, while machine-learning algorithms gave estimation results that span the range from the best to the worst cases. This clearly confirms the difficulty in training machine learning algorithms.

In the emergency case, the extreme values in the dataset surprised most participants, and much more variability was observed in the results: the correlation coefficient ranged from 0.02 to 0.86 and most values fell below 0.50. In a number of cases, geostatistical techniques failed to generate any results due to the heavy dependence on the model of spatial correlation that could not be calculated. Contrary to the first case, the few algorithms which gave excellent results were solely machine learning algorithms.

Conclusions

Drawing any general conclusions from these few case studies would be adventurous. One will nevertheless note that, as in SIC97, none of the SIC2004 participants used an existing Geographic Information System (GIS) whose interpolation functions often appear as black boxes to the user and/or because the proposed functions are too sim-

plistic. However, this situation is improving thanks to the growing awareness of GIS users.

Geostatistical techniques will probably need to become even more complex than they are at the moment in order to be able do deal properly with very local, extreme events. However, they still remain interesting candidate functions as they are often used to generate so-called risk maps in which the probability of exceeding a given threshold is calculated. Furthermore, in the case of large-scale events and when the number of reporting stations becomes large enough to define a dominant spatial structure of the monitored phenomenon, one would probably obtain excellent results with geostatistical techniques. Here, self-learning algorithms would seem to have a more promising future if they did not generate so many false alarms! In other words, any increase in the values observed would have triggered an alarm and generated alarm maps. What is certain is that many more case studies need to be considered and tested before any of these algorithms can be effectively implemented today in a decision-support system. As more scenarios can be tested, research in comparing systems for various types of hazards will probably improve the design of algorithms.

Practically, for what concerns the German monitoring network, the very high density of monitoring stations compensates for the lack of an efficient mapping algorithm. The system uses triangulations (Triangulated Irregular Networks, TIN) in which the surface is represented as a set of contiguous, non-overlapping triangles. Maps can thus be drawn in real-time and, as no extrapolation is possible, the interpolator neither smoothes out extreme values nor does it trigger false alarms.

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