A GEOVISUAL ANALYTICS APPROACH TO SPATIAL MULTIPLE OBJECTIVE OPTIMIZATION

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Abstract

Multiple objective genetic algorithms (MOGA) are heuristics that have seen relatively little use in geographic information science and spatial decision support in comparison to other geocomputational methods, despite their potential to generate robust alternative options for decision making. MOGA based decision analysis relieves the burden of a priori preference specification by an analyst, but the resulting solution set is potentially large and one must sift through many feasible alternatives in an intelligent manner. Since the task of evaluating the alternatives can be cognitively difficult there is a need for visual and analytic approach to aid the decision option selection process. One solution based on such an approach and proposed in this paper is the integration of MOGA with geovisual analytic tools.

Keywords: genetic algorithms, spatial optimization, geovisual analytics, multiple criteria evaluation, GIS, spatial decision support

Introduction

Two crucial tasks in computational approach to spatial decision support are: (1) design and (2) evaluation. The task of design involves generating feasible decision options (alternatives) and the task of evaluation requires combining the preference structure of decision maker with performance characteristics of decision options to aid the process of choosing the decision alternative. While methods and applications of spatial multiple criteria evaluation are relatively well known (Malczewski 2006) the use of geocomputational methods supporting spatial decision option design is more recent and still under development. In the latter category multiple objective spatial optimization has been the dominant approach (Malczewski 2006). Multiple objective spatial optimization problems can be solved either exactly using integer programming methods (Aerts et al. 2003, Ligmann-Zielinska et al. 2008) or approximately using heuristic methods such as evolutionary algorithms (Xiao et al. 2007). The former are limited to small-size problems, which is not the limitation of heuristic optimization methods. The latter are capable of generating a relatively large number of non-inferior (i.e. Pareto-efficient) solutions in a reasonable computational time. These solutions, however, result in a number of trade-offs, which should be evaluated by a decision maker or an analyst assisting the decision maker. This requirement increases considerably a cognitive burden placed upon the users of evolutionary algorithms. In order to lessen this burden Bennett et al. (2004) proposed a system composed of maps and plots of trade-offs among the objective function values. Xiao et al. (2007) extended this work by including small multiple maps of various categories of similar solutions and providing the scatterplot matrices of the objective function space. Their system was implemented using a loose coupling strategy (Jankowski 2006, Malczewski 2006). The work presented in this paper extends the research of Bennett et al. (2004) and Xiao et al. (2007) by developing a tightly coupled integration of geovisual analytics with a MOGA solver. The design framework guiding the integration is based on three assumptions: (1) a MOGA can produce a diverse set of decision alternatives, (2) the subsequent use of an exploratory Multiple Objective Decision Analysis (MODA) can reduce the set of decision alternatives to a small number of non-dominated (Pareto-efficient) solutions, and (3) Multiple Attribute Decision Analysis (MADA) can be applied to further explore trade-offs among the efficient solutions, ultimately helping to make a choice. The objective of research reported in this paper is to demonstrate that a geovisual analytics approach, achieved by a tightly coupled integration of MOGA solver with exploratory MODA and MADA tools, can provide an effective support in locational decision problems where an acceptable solution is a function of multiple and often competing objectives.

Methodology

A tightly coupled integration of MOGA solver with MODA and MADA tools involves a metaheuristics software library including a number of multiple objective genetic algorithms (Durillo et al. 2006) and Geospatial Visual Analytics Toolkit that offers exploratory MODA and MADA tools (Andrienko and Andrienko 2008). The integrated system supports a generative-exploratory workflow, in which multiple objective spatial optimization models are solved by MOGA resulting in a set of Pareto-efficient solutions. Trade-offs among these solutions can be subsequently visualized on trade-off curves linked with thematic maps (Lotov et al. 2005, Andrienko and Andrienko 2003). Trade-off curves help an analyst to locate key trade-offs among any two objectives and relate these trade-offs to measurable characteristics of Pareto-efficient solutions. Linking the trade-off curves with thematic maps provides a capability to immediately visualize the locations of solutions corresponding to specific trade-offs. The advantage of this exploratory approach to trade-off analysis is a user-driven, rather than an algorithm-driven (black-box) pruning of a potentially large set of Pareto-efficient solutions. Once the reduced set of interesting solutions has been selected, the problem of choosing a decision alternative is evaluated further with Multiple Attribute Decision Analysis (MADA) techniques. MADA techniques rely on ancillary geographic data, not included in a multiple objective optimization model, to derive evaluation criteria for further screening of the reduced set of Pareto-efficient solutions. The multiple criteria evaluation is an interactive process, in which the evaluation results can be visualized on charts including parallel coordinate plots and scatterplots linked with maps depicting locations of Pareto-optimal solutions. The analyst can then explore the effects of changing priorities assigned to specific evaluation criteria on the rank-order of Pareto-efficient solutions and their spatial arrangement.

Spatial Decision Problem: design of a monitoring network of ground based sensors

The efficacy of the proposed approach is demonstrated on the example of designing a monitoring network of ground based sensors. Sensors in such a network may provide an early warning of anomalous conditions that indicate, for example, a higher than acceptable pollutant concentration or heightened seismic activity. The geographic configuration of the network with respect to the scale of spatial process and autocorrelation of a measured variable can have considerable impact on the quality or uncertainty of resulting models and maps. The decision problem here is to determine where to place the sensors so that pollution concentration can be interpolated for the entire region and the areas immediately affected by a pollutant release, within acceptable error thresholds, and at an acceptable cost of deploying and maintaining the sensors.

The design of sensor network configuration can be formulated as a three-objective optimization problem where the decision objective functions are:

1) Minimize the number of sensors
2) Minimize the Mean Universal Kriging Prediction Error Variance (MUKPEV)
3) Minimize MUKPEV in areas that are covered by simulated plumes of pollution.

The decision problem is then to determine a trade-off between removing (thinning) sensors from the network and increasing the prediction error variance to an acceptable level. Such a formulated decision problem was analyzed in the context of the European Radioactivity Environmental Monitoring Network. The network is comprised of 649 sensors (see Figure 1) located in the Netherlands and two western states in Germany (North Rhine Westphalia and Lower Saxony). A variogram of Gamma Dose Rates (a measure of radioactivity collected by the sensors) was obtained from simulating radioactive plumes of nuclear plant release under varying atmospheric transport conditions. The variogram was used in a kriging model to compute function values for decision objectives 2 and 3.

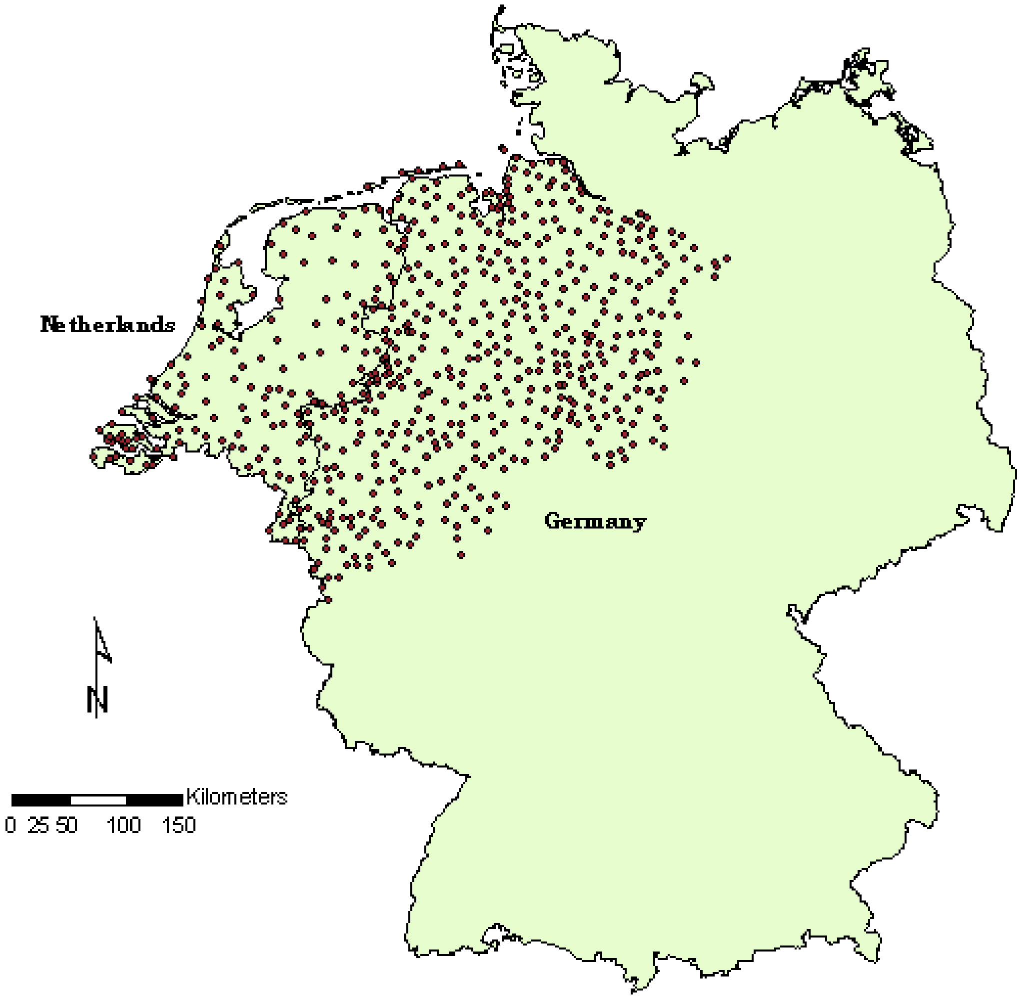

Figure 1. Locations of 649 sensors in the Netherlands, North Rhine Westphalia and Lower Saxony (Germany).

The set of non-dominated (in the Pareto sense) solutions was generated by running NSGA-II algorithm (Deb 2001) with a population size of 50 over 20 generations. The crossover probability was set to 0.9 and the mutation probability was 0.2. A two-point crossover was used, meaning the chromosomes were split at two points and then their portions swapped. A bit-flip mutation was used, meaning genes were randomly perturbed by changing their values from 0 to 1 or from 1 to 0. The chromosome used here is a string of 1s and 0s, where each digit represents a sensor from the original set. If the sensor corresponding to a particular bit has a value of zero then it is not present in the solution, and conversely if it has a value of 1 then it is present in the solution.

The feasible goals method and the decision map technique (Lotov et al. 2005, Andrienko and Andrienko 2003) were used to graphically represent the Pareto-efficient trade-off frontiers for 50 solutions generated by MOGA. The number of sensors in these solutions ranges from low 295 to high 341. For the selected number of sensors ranging from 295 to 341 an analyst can visually evaluate a trade-off between MUKPEV for the entire study area and MUKPEV for the area covered by the radioactive plume (see Figure 2). Looking at the decision map in Figure 2 one can see that the high number of sensors (represented by blue and magenta trade-off frontiers) corresponds to relatively low MUKPEV values and conversely the low number of sensors (represented by yellow, orange and red trade-off frontiers) corresponds to high MUKPEV values.

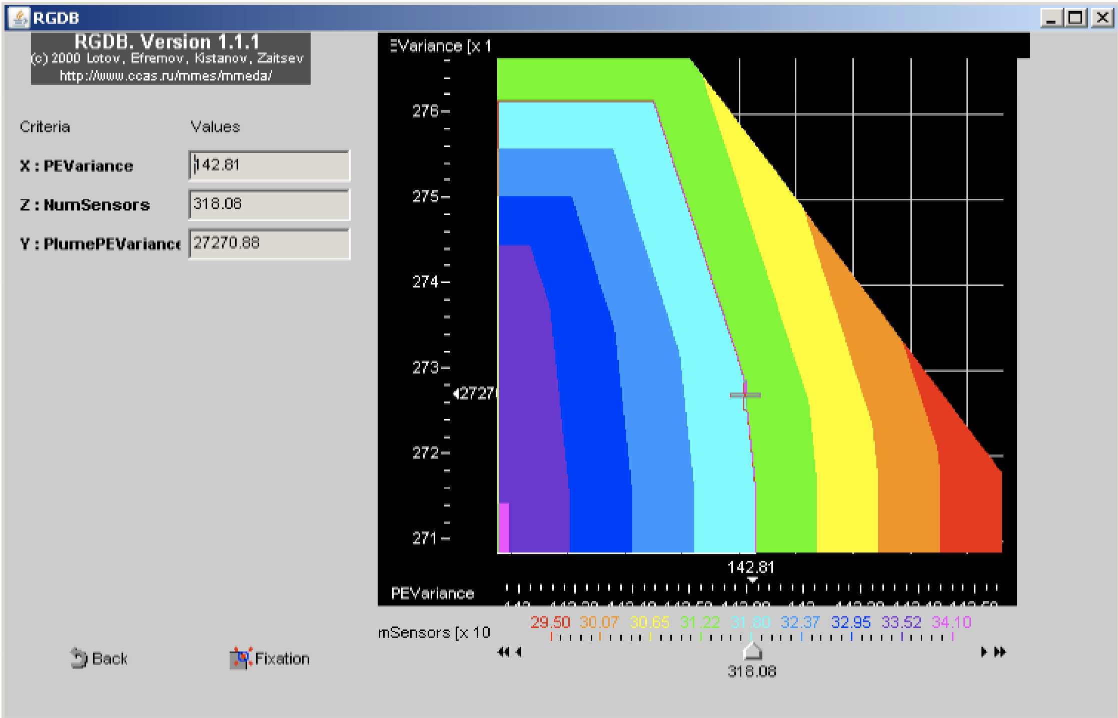

Figure 2. Decision map for examining trade-offs between MUKPEV for the study area and MUKPEV for the plume-covered area. The value of the third objective function – the number of sensors can be selected interactively by the analyst by moving the slider at the bottom of the graph.

Each trade-off, indicated by the position of cross-hair on the trade-off frontier, corresponds to a specific solution comprised of a subset of sensors. An analyst can visually evaluate fit between a specific solution and spatial selection criteria not incorporated in the problem objective functions. Such criteria may include, for example, the type of land use and population density. Here, the European Corine land cover dataset was reclassified to two land use types: agriculture and non-agriculture. A raster layer of population density was also acquired. These two spatial criteria were used in multiple criteria decision analysis with the idea that areas with high percentage of agricultural land use and high population density should be preferred over other areas. The logic behind this is that it is important to know with a reasonable level of accuracy what concentration of radioactivity can be expected in areas vital for food supply (agriculture) and in population centers. The visual analytics toolkit was used to create a fishnet discretization of the study area and to rank-order each rectangular unit of land based on the weighted aggregation of agricultural land use percentage and the population density in each rectangle (see Figure 3).

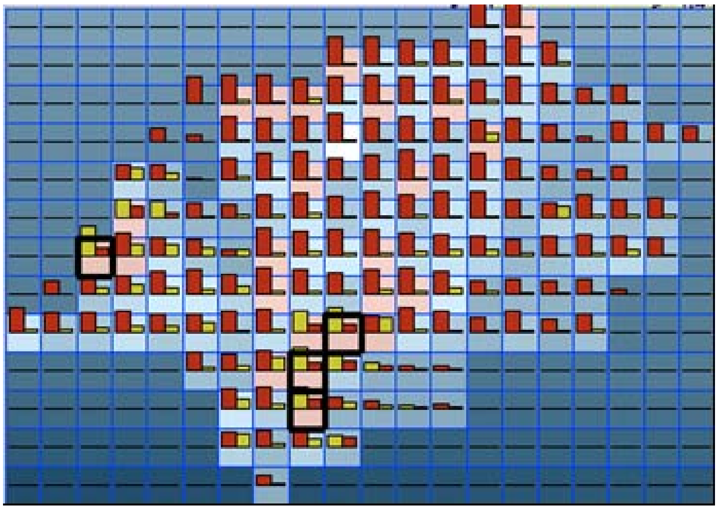

Figure 3. Red bars represent the percentage of agricultural land within each rectangular unit of land, while yellow bars represent a relative (to the study area) population density. A diverging color scheme, from light red to blue-gray, is used to symbolize the rank of land unit with light red representing highly ranked and blue-gray representing low-ranked rectangles.

The highly ranked (light red) rectangles are characterized by either a high percentage of agricultural land or high relative population density or a combination of both, such as four rectangles selected in Figure 3.

The land units can then be overlaid with optimization solutions, comprised of sensor configurations, in order to visually inspect the goodness of fit between high priority areas (highly ranked land units) and specific MOGA solutions (see Figure 4). The map in the left part of Figure 4 depicts one specific solution comprised of a subset of 318 sensors overlaid on the rectangular fishnet covering the study area. The map depicts spatial distributions of two objective functions: (1) minimization of the number of sensors, and (2) minimization of MUKPEV, where the values of the latter, expressed in Sv/h, are symbolized by a full spectral color scheme ranging from yellow (low interpolated radiation variance) to red (high interpolated radiation variance). The map in the right part of Figure 4 shows the rank-order distribution of land units overlaid with the subset of 318 sensors. One can then visually inspect a selected MOGA solution (in the left part of Figure 4), cross-reference it with MADA solution (in the right part of Figure 4) and determine the concordance of both solutions. Concordant solutions, which represent an acceptable compromise between the result of multiple objective optimization and spatial multiple criteria evaluation may help to select the sensor network configuration.

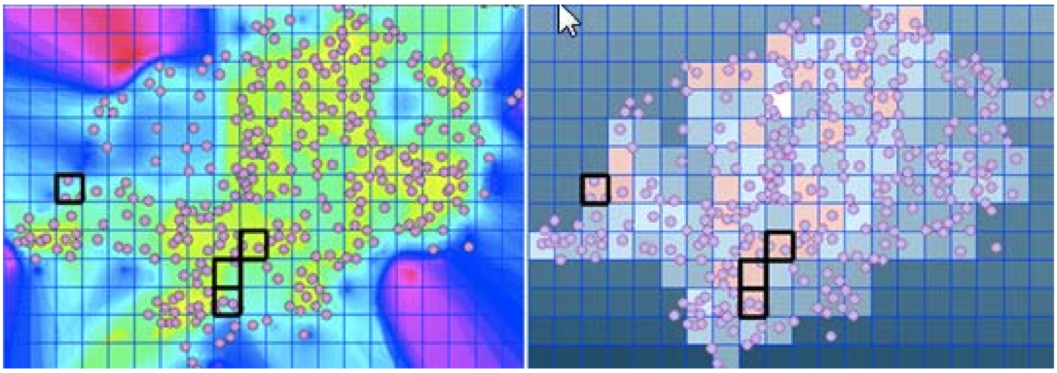

Figure 4. On the left, 318 sensors represented by dots and Mean Universal Kriging Prediction Error Variance (MUKPEV) symbolized by the full color spectrum are overlaid on fishnet tessellation of the study area. On the right, the fishnet rectangles rank-ordered from high (light-red) to low (blue-gray) are overlaid with the same set of 318 sensors.

The future extension of the above presented visual analysis approach will offer quantitative measures of assessing the fit between multiple objective optimization solutions and spatial multiple criteria evaluation of land units.

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