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VISUALIZATION OF DATA FROM NETWORK OF SENSORS: APPROPRIATE SPATIAL INTERPOLATION METHOD

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Abstract

Graphical presentation of the measured data is more popular than ever before. However, rich and colourful images are often misrepresentation of the measured quantities. In this paper we discuss proper mathematical technique for correct presentation of data from the network of sensors. Three common methods for spatial interpolation are demonstrated and compared using real data from the network of sensors (for air pollution with aerosols). Finally, best procedure is recommended and discussed in details.

Keywords: network of sensors; spatial interpolation; Hilbert space; air pollution

1. Introduction

Number of sensors of various types that are connected to the internet is increasing rapidly. This fits into trends popularly called "Internet of Things" and "Smart Cities". Despite the fact that number of sensors is increasing, we will never have a sensor at every single point of interest. Therefore, some sort of spatial interpolation is needed. The main question is: if we have N sensors over certain geographical area, which spatial interpolation method is appropriate for visualization of measured quantity over the entire area? In this paper we will try to answer that question using the real data from the network of sensors that measure air pollution.

The simplest approach is to use **bilinear interpolation** [1]:

$$f(x,y) = a_0 + a_1 x + a_2 y + a_3 xy \tag{1}$$

where a_0, a_1, a_2 and a_3 are coefficients which can be calculated by knowing values of function f at four different points around (four sensors from the network). Obviously, this is not the best method, due to the nature of sensors (inevitable errors during the measurements) and local disturbances (very localized source of air pollution for example).

More natural approach is **inversed distance weighting** [2]. This is a multivariate interpolation with a known scattered set of points. The assigned values to unknown points are calculated with a weighted average of the values available at the known points. This method gives few options of choosing parameters, so that the nature of the measurements is represented properly.

Next candidate is the procedure called **kriging** [3] (name given from the master thesis of Danie Krige [4]). Kriging is a method of interpolation for which the interpolated values are modelled by a Gaussian process governed by prior covariance. The kriging estimation may also be seen as a (sort of) spline in a Hilbert space. When performing kriging, the user must specify the function which describes the degree of spatial dependence of a spatial random field – this is called variogram. Under suitable assumptions, kriging gives the best linear unbiased prediction of the intermediate values [5].

2. Case study

Network of 13 sensors which measure the concentration of aerosols smaller than 10 μm (PM10) was installed in and around the city of Sarajevo. Daily average values of PM10 for 30/08/2018 are chosen for this study. Figure 1 illustrates the location of sensors, while table 1 shows calculated average values of PM10 for each sensor. The method for data acquisition is explained in [6] and [7], while the calibration of PM10 sensor was described in [8].

Fig. 1. Location of sensors

sensor	latitude	longitude	PM10 (μg/m^3)
1	43.89488	18.37228	33.51
2	43.82361	18.54752	26.09
3	43.86172	18.41277	34.47
4	43.84860	18.37393	39.53
5	43.85390	18.39553	37.80
6	43.85284	18.38026	41.12
7	43.84482	18.32074	41.66
8	43.85846	18.44020	32.04
9	43.86775	18.42296	33.27
10	43.95983	18.27251	47.09
11	43.94594	18.25530	46.14
12	43.85121	18.36727	41.40
13	43.82605	18.34702	40.01

Table 1. Daily average values of PM10 for 30/8/2018

3. Spatial interpolation methods

Bilinear interpolation was applied in figure 2. Akima library for R programming language was used for calculations of interpolated values. Contour lines (for values of PM10) were added, together with locations of sensors. There is no interpolation outside the polygon of sensors. We can also see that this spatial interpolation of PM10 doesn't look natural because values from sensors around the city linearly propagate all the way to the city center.

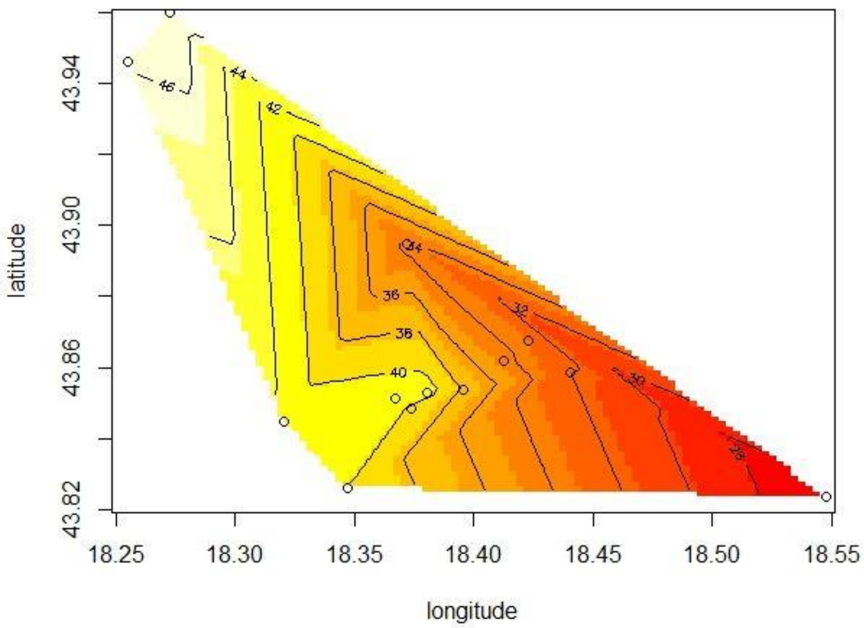
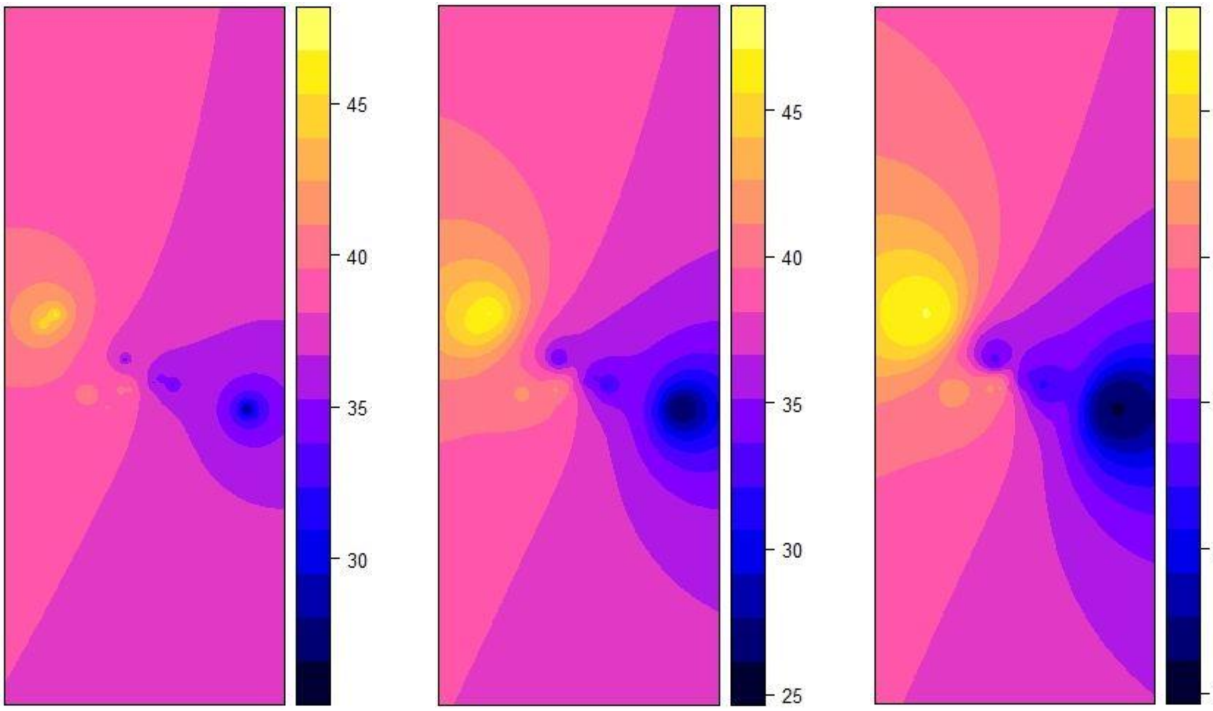


Fig. 2. Bilinear interpolation

Figure 3 shows inverse distance weighting (IDW) interpolation with three different power factors (1, 2 and 3). Calculations were performed in R programming language again. Contour lines look more natural now. However, we don't know *a priori* which power factor is correct.



$p = 1$ $p = 2$ $p = 3$

Fig. 3. Inverse distance weighting interpolation with three different power coefficients

Now we proceed to the kriging. As noted above, first thing we need to do is to choose the proper variogram. Figure 4 shows the dependence of semivariance on distance, for the selected dataset. We can see from the graph that the Gaussian fit is the best option. Using the Gaussian fit from figure 4 we can finally perform kriging interpolation. Figure 5 shows the result of this operation. We can also estimate quality of interpolation by means of cross-validation: it removes each data location, one at a time and predicts the associated data value. R programming language was used for plotting kriging interpolation and cross-validation errors in figure 5. We would like to note that IDW and kriging techniques can be used to extrapolate data as well. Please note the location of sensors in figure 1: we can't have good estimation in the region where we don't have sensors at all!

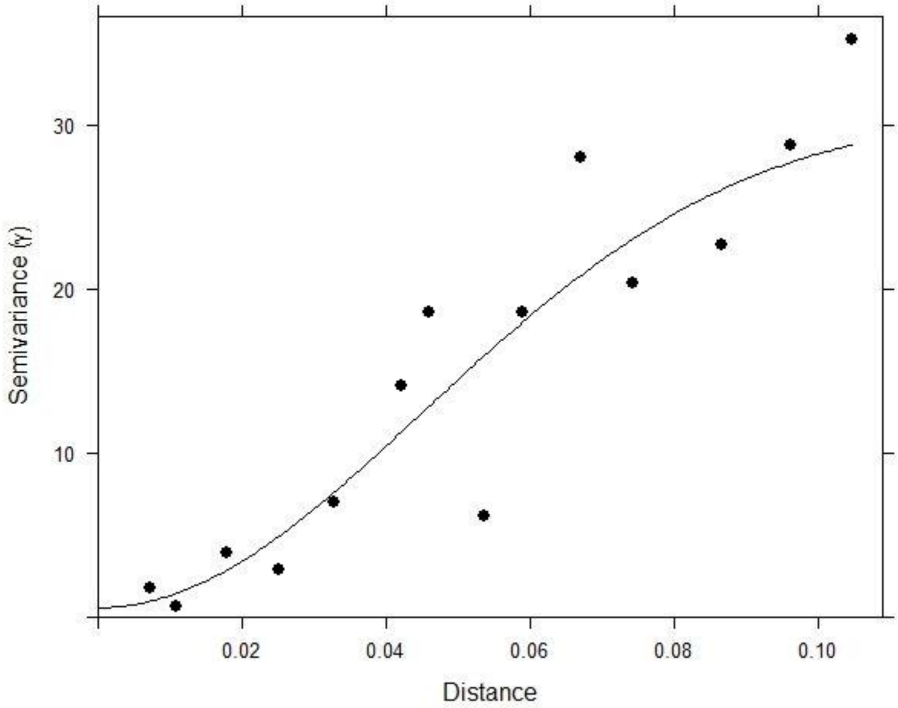


Fig. 4. Variogram and Gaussian fit

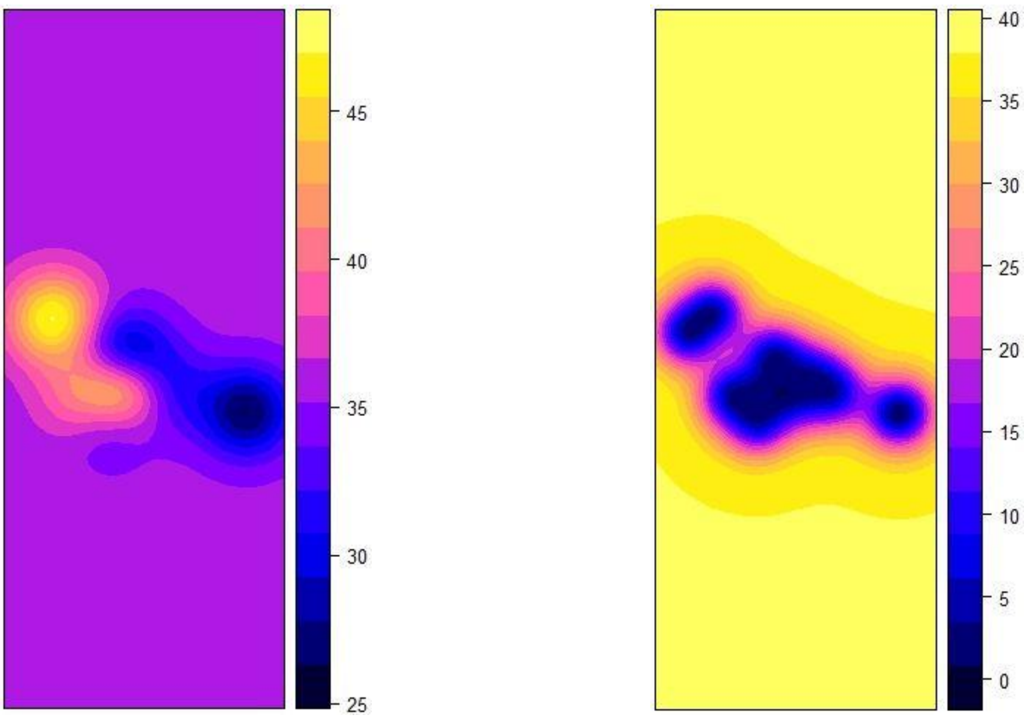


Fig. 5. Kriging interpolation and cross-validation

4. Conclusion

Three different techniques for interpolation of data from network of sensors were analysed: bilinear, IDW and kriging interpolation. They produced significantly different contour lines of PM10 concentrations from the same dataset. Bilinear interpolation should not be used for such cases (where we have non-trivial spatial correlation of data). IDW interpolation gives more natural contour lines, but it requires parameters that we don’t know *a priori*. The final conclusion is very clear: kriging is the preferable method. If the variogram fit is chosen properly, kriging is the best interpolation technique among these three (and probably best of all, for most general applications).

As a suggestion for further research we propose:
- Extension of network of sensors to more different places,
- Measurement of various episodes of air pollution, especially during the winter,
- Analysis of more variables such as altitude, humidity etc.

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