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Investigating Landfill Contamination by Visualizing Geophysical Data

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Geophysical experts were studying a landfill in the suburbs of Porto. They aimed to develop a method to detect anomalous volumes in the subsoil corresponding to contamination of the landfill. Instead of chemically analyzing continuous subsoil samples, which is time-consuming and comparatively expensive, the analysis employs nonintrusive 2D electrical resistivity (ER) data acquired on the landfill site.

To assist them, we developed an application that analyzes and visualizes ER data. The application interpolates the measured 2D ER profiles to provide a volumetric representation of the subsoil. Then, it uses statistical criteria coupled with 3D visualization to represent areas with a high probability of contamination. Statistical methods provide a threshold between normal and anomalous ER values based on ER distributions. This threshold might change from site to site, owing to geological variations unrelated to contamination or owing to depth (rocks' physical properties can change with depth and soil materials). So, users can interactively subdivide the dataset into sublevels of similar properties parallel to the surface. This is a new capability; the traditional solution uses a fixed threshold for the statistical distribution of subsoil property variations with depth.

Our application also interactively displays the uncertainty at each point in the volume. This is particularly relevant in our case because interpolation must be used with caution, given the data's sparseness.

Geophysical Data and Methods

To obtain 2D sections of the ER data, the geophysical experts measure each value along a line on the surface. To do this, they use four electrodes: two to inject current and two to read potentials. Initially, the spacing between the electrodes is small (typically between 2 and 3 meters, according to the available space). After each measurement, the electrodes are automatically displaced laterally until they reach the end of the desired profile. Next, the spacing between the electrodes increases, which increases the depth penetration. The automatic displacement is possible because the measurement line consists of several electrodes and the process can switch automatically between the injecting and reading electrodes without moving them physically. Figure 1 shows this process.

Special software then inverts the set of acquired measurements to find the terrain model that best fits the measured ER. Basically, the obtained field data are a surface response of the subsurface model. To begin the inversion, the software automatically generates a starting model estimated from rough depth and resistivity relationships. This model lets the software generate synthetic field data, which it compares with the real field data. The first estimate always has a relatively high misfit. So, the software

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iterates through changes in the subsurface model and generates new synthetic field data, which it again compares with the real data. This process continues through least-squares optimization until the error is minimized. At this point, the software has found the 2D ER depth model of the soil.

Figure 2 presents a 2D section (perpendicular to the geophysical field's topographic surface) resulting from the inversion. Typically, a study of a specific area acquires several of these grids (also called electrical grid sections or just ER sections). ER values (measured in ohm.meters) are continuous and scalar; they vary according to the subsoil material and water content and because of the presence of chemical inorganic contaminants. In this case study, the landfill was 0.49 km^2, and the experts measured 32 2D profiles from 94 to 141 m long.

Electrical-Resistivity Interpolation

Because ER data is sparse (consisting of 2D sections acquired in different directions and positions, as we'll show later), experts want a volumetric representation of it to ease their analysis and more easily correlate the spatial information from different sections. However, subsoil properties usually don't follow a simple linear distribution; interpolation based on the *regionalized variable theory* (RVT) achieves better results. RVT is a geostatistical method based on the idea that interpolation of points in space shouldn't be linearly estimated but should consider the statistical relationships in the dataset.

The RVT algorithm we selected is ordinary *kriging* because it produces good results with geophysical data and is commonly used by experts in this context. To predict a function's value at a given point, kriging computes a weighted average of the known values in the neighborhood. Ordinary kriging first constructs a variogram by calculating the variance of each point in the set with respect to each of the other points. On the basis of the variogram, we can define a mathematical function that models the trend in the variogram and use it to compute the weights for the interpolation. Kriging typically produces the best results for geophysical data.[2] (The results are 20 to 30 percent better than simple methods such as inverse distance weighting, which directly relates the interpolation's weights to the distance between neighboring points.)

Anomaly Calculation

In this case study, the domain experts aimed mainly to detect an anomaly corresponding to an unusual concentration of a particular set of contaminants in the groundwater environment. For the Porto landfill, such an anomaly might

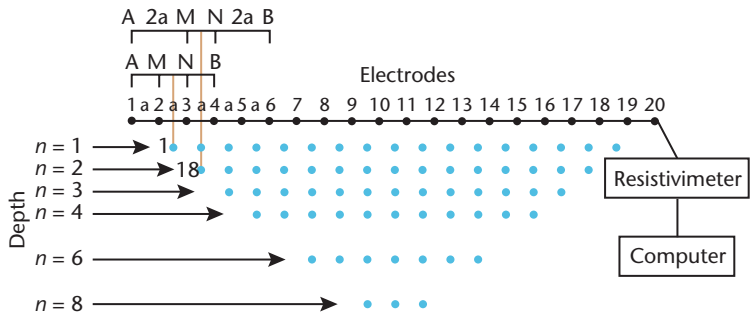

Figure 1. Constructing an electrical resistivity (ER) pseudosection with a Wenner-Schlumberger sequence.[1] As the distance between the injecting electrodes (A and B) and reading (M and N) electrodes increases, so does the depth of the measured points (the blue dots).

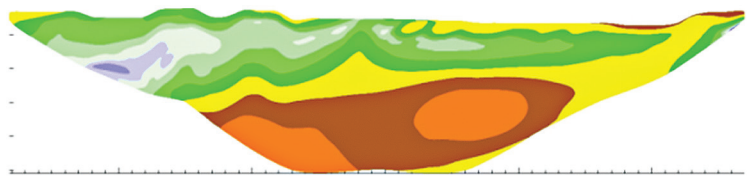

Figure 2. A 2D ER section after inversion. Typically, a study of a specific area acquires several of these grids.

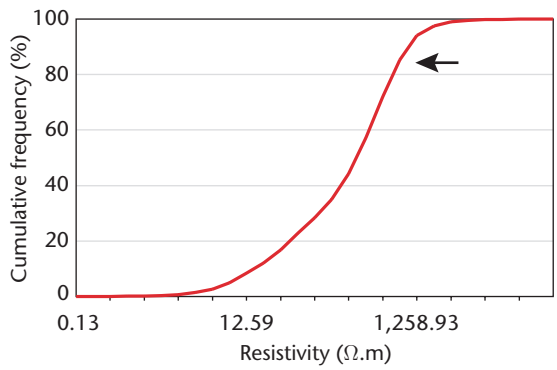

Figure 3. The Lepeltier method. The arrow indicates the turning point between the background and anomaly.

indicate the landfill's leakage into the surrounding area.

The concepts of anomaly and background are inextricably linked, and domain experts often use statistical techniques to distinguish between them for mineral exploration. For geochemical background and anomalies, experts usually implement a methodology based on Claude Lepeltier's research.[3] This methodology assumes that the concentration of elements has a log-normal distribution. It plots the cumulative frequency versus element concentration (in bilogarithmic scale), as Figure 3 shows. An inflection at the top of this curve indicates an anomaly.[3,4] To numerically represent this inflection point, we use the value of the

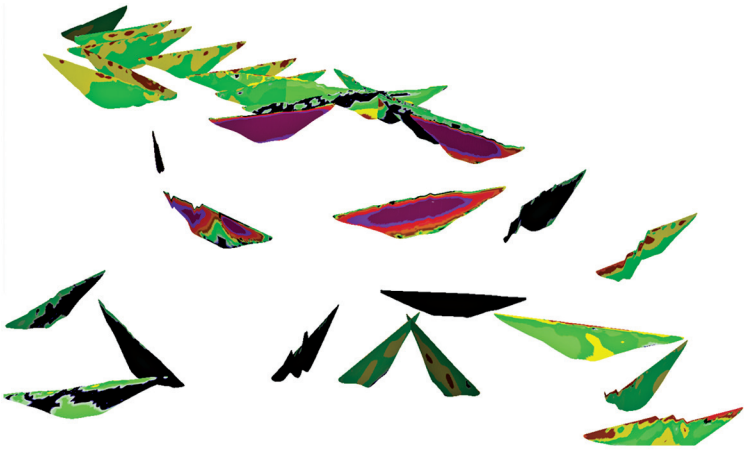

Figure 4. 2D ER sections in 3D space, with an anomaly (in black). Positioning the 2D sections in their real 3D space makes it easier to perceive possible continuities and trends.

Unlike traditional geophysical software, our application displays the 2D ER sections in their real 3D positions.

mean + 2 standard deviations (σ) of the population. Using the iterative 2σ technique, we remove all values beyond the mean + 2σ until we obtain a normal distribution. The removed values are the anomaly; what remains is the background.

Adapting this methodology to geophysical data comprising a large set of resistivity sections sampled over a wide area, we obtain a statistically defined limit for what should be the anomalous value limit. This differs from common practice, which simply defines an arbitrary resistivity value based on empirical experience. However, we don't apply the algorithm to the whole dataset at once because rock properties (such as porosity and permeability) vary with depth. To handle these variations, experts perform a preliminary observation of the data. They visually and interactively assess the number of levels and thus define the section ranges to analyze for anomalous and background levels. 3D visualization can greatly ease this process.

The Application and Visualizations

We developed our application to provide the experts with a single tool that performs all the data processing (normally done with several applications) and directly generates correctly aligned 3D visualizations of the data instead of 2D sections. We developed the application in C++. For the visualization library, we used the Visualization Toolkit. The application uses polygonal meshes to visualize ER sections and terrain surfaces, and volume rendering to represent interpolated ER data and anomalies.

Visualization of 2D Sections

First, we integrated 2D sections into the application, for two reasons. First, experts are used to working with them. Second, they allow detailed analysis of individual electrical sections without 3D manipulation, which can be confusing.

We adopted a rainbow color scale, in spite of its disadvantages,[5] because experts are familiar with it and it provides an intuitive interpretation. Colder, blue tones indicate lower resistivity—areas more likely to have water. The warmer yellow, brown, or red tones indicate more resistive lithologies that usually correspond to more compact and less porous rock. Greens indicate intermediate zones.

After an extensive discussion with the experts, we chose black to represent anomalous values in ER data because it doesn't collide with the color scale and is easy to perceive. We obtained the anomaly with 15 depth intervals. We applied topographic correction because the acquired ER sections were measured relative to the terrain surface (which corresponds to zero depth) to ensure a correct alignment of data relative to depth.

Visualization of 2D Sections in 3D Space

Unlike traditional geophysical software, our application displays the 2D ER sections in their real 3D positions. This makes it easier to perceive possible continuities and trends. The application positions the sections on the basis of their coordinates. Figure 4 shows several sections in their correct 3D position with the anomaly.

Volume Visualization

The application takes the 3D volume representation resulting from kriging interpolation and aligns it with the terrain. It initializes the 2D sections in the correct positions, given their starting and ending coordinates. It renders the terrain topology and voxels that might fall above the terrain surface (owing to topology corrections) with zero opacity.

Each time the application calculates the anomaly using different parameters, it dynamically generates a new volume. For example, the user might give a different division of the subsoil, resulting in different depth intervals and thus a different subregion to analyze. Generation of the new volume lets the user easily inspect how those intervals influence image quality and rendering time. We use ray casting because it produces a good trade-off between image quality and rendering time.

Figure 5 shows the results of interpolation and anomaly calculation for the data in Figure 4. Figure 5a shows the resistivity volume without the anomaly, 5b shows the volume with the anomaly, and 5c shows only the anomaly and 2D ER sections. The experts required the visualization in Figure 5c because they needed a clear view of the anomaly to better understand trends in the possible contamination. These volumetric representations facilitated the interpretation of the phenomenon by providing a general view of the anomaly's position or area that the experts couldn't easily obtain with other spatial-analysis tools.

The application also lets users compute some quantitative measures that weren't previously obtainable. For example, they can easily approximate the anomaly volume on the basis of the number of anomalous voxels.

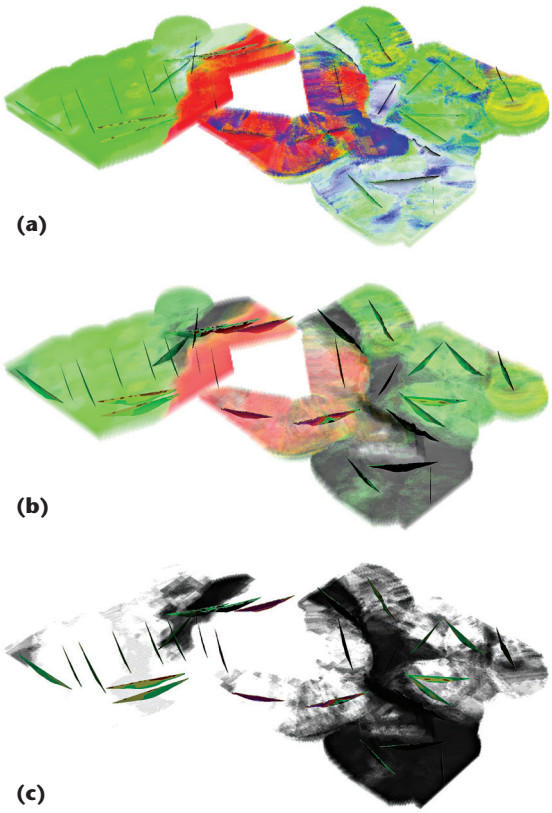

Figure 5. Volumetric representations of ER for the data in Figure 4, (a) without the anomaly, (b) with the anomaly, and (c) with only the anomaly and 2D ER sections. These representations provided a view of the anomaly that the experts couldn't easily obtain with other spatial-analysis tools.

Visualization of the Terrain Surface

The domain experts particularly appreciated the ability to map the studied area's surface. This provided context that let them relate the data and anomaly with the terrain surface information and topography. In particular, mapping satellite images of the area gave them immediate context and visual references to better understand the studied phenomenon's location.

Figure 6 shows several ER sections in 3D space with the anomaly and a textured polygonal mesh representing the topographic terrain surface. To obtain this isosurface, we applied a Delaunay triangulation to the terrain model's 3D coordinates (considering a null z coordinate). We draped a georeferenced texture image of the area over the surface to ease the interpretation of the anomaly's position relative to the terrain.

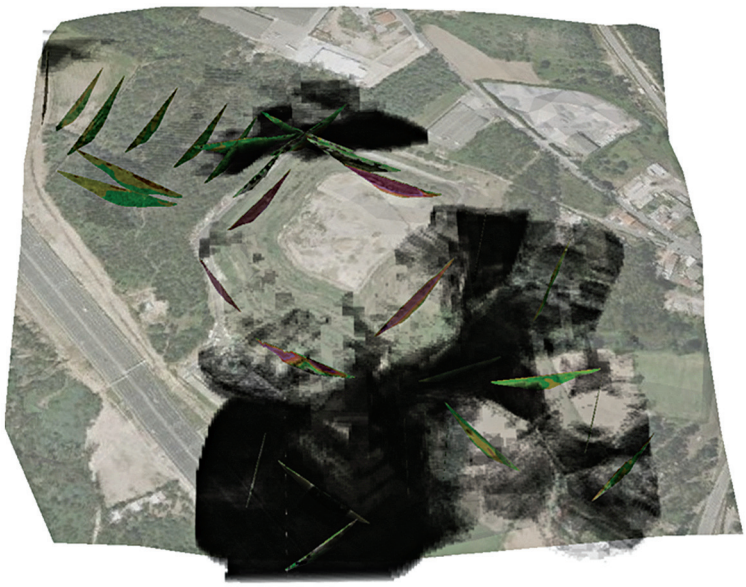

Figure 6. A textured surface with ER sections underneath; the anomaly is projected in black on the surface. We draped a georeferenced texture image of the area over the surface to ease the interpretation of the anomaly's position relative to the terrain.

Interactive Visualization of Uncertainty

Most commercial software packages used in geoscience (and other areas) don't consider uncertainty in visualizations. This might lead to errors and misunderstanding, particularly when large portions of data are interpolated, as in our study. Representing uncertainty is difficult because it's a 4D problem typically coded by either using an additional representation for it (such as a glyph or blur) or integrating it in the data (through color or opacity).[6,7]

We performed preliminary tests using techniques such as blurs or additional glyphs. However, the experts weren't very interested because those representations increased the complexity of an already cluttered visualization. So, we made uncertainty visualization interactive so that they could control the degree of interpolated data they

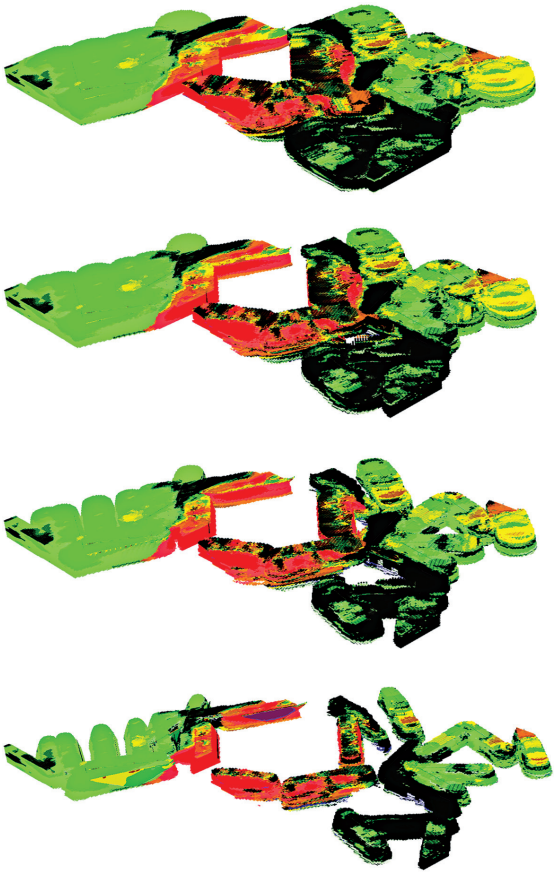

Figure 7. Interactive visualization of the uncertainty related to data interpolation, with uncertainty (opacity) decreasing from top to bottom. Users can specify the uncertainty level through a slider; the opacity transfer function changes accordingly.

wanted to analyze, according to uncertainty. This approach avoided data distortion and additional visual representations and gave them control of the visualization of uncertainty.

The application computes uncertainty as a function of the distance to the closest section; that is, interpolated data farther from the actual profile is more uncertain. In the 3D volumetric data, this corresponds to associating two scalars to each voxel: one for resistivity and one for uncertainty. We map resistivity through color and uncertainty through opacity. Users can specify the uncertainty level using a slider; the opacity transfer function changes accordingly (see Figure 7), resulting in full transparency of all voxels with uncertainty above the threshold. At the highest limit, the application shows only 2D profiles, similarly to Figure 4. Figure 7 presents four representations of the same volume with different uncertainty thresholds.

Validating the Results

To validate the statistical method the experts used to compute the anomaly, they collected water samples from a few piezometers at specific boreholes in the landfill. They chemically analyzed the samples to assess the groundwater contamination's extent.

Using these measurements and their locations, we inserted validation samples into the visualizations. These samples appeared as colored cylinders:

- Red indicated major contamination (the ER was less than 25 ohm.m).
- Yellow indicated minor contamination (the ER ranged from 25 to 50 ohm.m).
- Green indicated no contamination (the ER was more than 50 ohm.m).

Figure 8 shows two visualizations including 2D sections, the anomaly volume, and the representation of the chemical samples.

Even though the number of samples was limited and taken only at specific borehole locations, the results confirmed that the software-generated anomaly correlated with the samples from the field. This supports the feasibility of using ER to create faster, more economical analyses of this type.

User Evaluation

The domain experts contributed actively to the application's development. After the first prototype was stable, we and three of them evaluated the method's and application's strengths and weaknesses.

The experts mentioned two important benefits. One was faster computation and easy quantification of the anomaly. They delineated the anomaly in about 30 minutes, compared to the 3.5 hours the analysis would have taken with traditional tools. The other benefit was that the 3D volumetric visualization of the topographically corrected ER was much more realistic than with other software packages they had used.

On the other hand, they had difficulty finding the best set of depth ranges to apply. We're still trying to find a more deterministic approach to this issue. They also suggested additional functionalities related to anomaly calculation. Examples include calculating various statistical parameters for each depth range, improved selection of each range, and a tool for viewing graphics or tables of the entire statistical analysis to help determine the best options.

Even though the application is still a prototype with several limitations, experts have installed it on their computers and used it to analyze datasets and produce visualizations.[8] Consequently, they've recommended features for later versions,

such as implementing other statistical interpolation methods and editing tools (for example, to delineate important structures).

To the best of our knowledge, our application is the first to offer both the ability to analyze and visualize ER data and tools to extract and represent anomalies in the 3D dataset. Our evaluation showed that this strategy significantly eased the experts' work. They could dynamically change both the statistical parameters of anomaly estimation (for example, the depth levels) and the anomaly estimation method and immediately obtain a visualization. Moreover, the 3D volumetric representation of the data and anomaly is a powerful technique that reduced the experts' cognitive workload.

We plan to integrate multimodal information to give experts a better understanding of the phenomenon and keep supporting their research.

Acknowledgments

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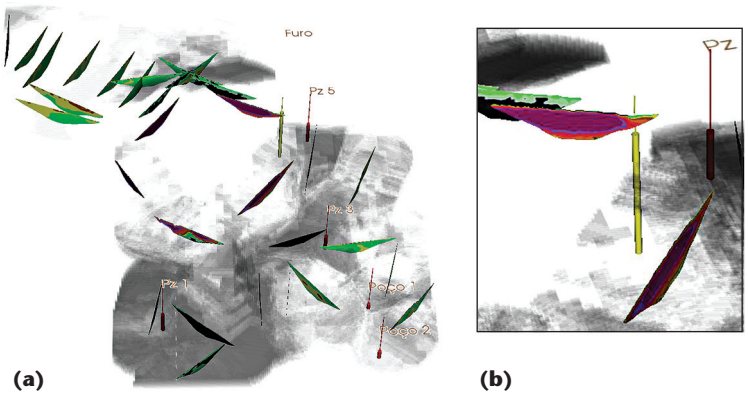

Figure 8. Chemical samples (represented by the cylinders) and the anomaly. (a) An overview of the whole area. (b) An area of interest with two samples. Red cylinders indicated major contamination, yellow indicated minor contamination, and green indicated no contamination.

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