Open-source learning as a skill for geoelectrical data processing: the case of pyGIMLi

Brayan Alexis Quiceno-Arenas [a], Juan Guillermo Paniagua-Castrillón [b, d], Andrés Mauricio Muñoz-García [c, d], Luis Fernando Duque-Gómez [b, d] & Moisés Oswaldo Bustamante-Rúa [e]

[a] Maestría en Automatización y Control Industrial, Instituto Tecnológico Metropolitano, Medellín, Colombia. brayanquiceno250856@correo.itm.edu.co
[b] Facultad de Ingenierías, Instituto Tecnológico Metropolitano, Medellín, Colombia. juanpaniagua@itm.edu.co
[c] Facultad de Ciencias Exactas y Aplicadas, Instituto Tecnológico Metropolitano, Medellín, Colombia. andresmunoz@itm.edu.co, luisduque@itm.edu.co
[d] Grupo de Geofísica y Ciencias de la Computación GGC3, Instituto Tecnológico Metropolitano, Medellín, Colombia. ggc3@itm.edu.co
[e] Universidad Nacional de Colombia, Sede Medellín, Facultad de Minas, Instituto de Minerales CIMEX, Medellín, Colombia. mobustam@unal.edu.co

Abstract
It is important that new strategies are developed for the management of geoelectrical data produced from engineering and geoscience processing techniques. For this reason, the article demonstrates how pyGIMLi can be used for this purpose. pyGIMLi is an open-source library for the inversion of apparent resistivity array that are often obtained with different geoelectrical survey equipment. The aim is to be able to use this library unaided for various projects and/or to perform various data operations in which the results obtained are more specific and differentiated than those derived from other processing techniques, taking advantage of the fact that this tool is open-source.

Keywords: learning in engineering; geosciences; open-source; pyGIMLi; geoelectrical data.

Aprendizaje de código abierto como habilidad para el procesamiento de datos geoeléctricos: caso pyGIMLi

Resumen
Debido a la importancia de utilizar nuevas estrategias para el manejo de datos geoeléctricos a partir de las técnicas de procesamiento de la ingeniería y ciencias de la tierra, este artículo se centra en mostrar la estructura para el uso de pyGIMLi, una librería de código abierto para realizar la inversión de la matriz de resistividad aparente que se obtienen a menudo con diferentes equipos de prospección geoeléctrica, con la finalidad de adquirir la habilidad de usar esta librería de forma independiente en diversos proyectos y/o realizar varias operaciones con los datos en las se puedan obtener resultados más específicos y diferenciados de otras técnicas de procesamiento; gracias a las ventajas de usar código abierto.

Palabras clave: aprendizaje en ingeniería; ciencias de la tierra; código abierto; pyGIMLi; datos geoeléctricos.

1. Introduction

The dependence on commercial software to process electrical data [1-3], including geoelectrical data, has certain consequences. The first is that the analysis of the results is affected by the very direct way in which these programs process them. The second is that it is not cognitively beneficial for the engineer processing the data because, in research, there should not be a gap between knowledge and application [4]. This is often the case when working with closed-source software, as it is difficult to understand the software's behavior and the information it has produced.

A promising alternative that addresses this situation is open-source software or environment, in which the same geoelectric data processing tools have been developed, but with code that can be seen, modified, and distributed freely

[4], or simply as part of environments provided by open-source platforms. This has stimulated new training strategies for working on the exploration and logistics stages of research on energy, minerals, and resources [5]. It has also strengthened engineering education in the undertaking of multiple tasks at the same time, such as the collection, processing, and analysis of data [6].

This is in clear contrast to the black box model, which is a fairly common type of closed-source software where no prior knowledge is required for its use and which often requires exploration to achieve new data analysis techniques. However, this exploration is not possible precisely due to its information-only input-output philosophy [7-10].

The purpose of this article is therefore to give a demonstration of geoelectrical signal processing for the exploration of mineral resources, and to illustrate the data structure and parameters by applying the useful features of the open-source environment pyGIMLi, with the aim of replicating the results and acquiring the ability to perform all of these processes correctly.

2. Data description

2.1 Localization

The geoelectrical data samples correspond to line-3 of an electrical resistivity tomography (ERT) profile taken in an area adjacent to drill hole 171 (PM-171 as seen in Fig. 1) on the open pit mining license of Inversiones WGM S.A.S. (Fig. 2) located in the hamlet of Margento, Caucasia, Antioquia, Colombia (Fig. 3).

2.2 Acquisition and characteristics

The ABEM Terrameter LS was used to take the samples, with electrodes fixed at a 5-meter initial center spacing and a standard lateral spacing (Fig. 4). A horizontal 5-meter offset was applied by ABEM on the surface to acquire the sample profile of each depth extension as seen in Figs. 5-7.

A total of 12 extensions of depth of investigation I_D were measured, hereafter referred to simply as depth. The maximum depth was approximately 33.8 meters. Fig. 8 shows the resistivity triangles (Ωm) that represent the entire distribution of samples acquired from each data line profile of the subsurface.
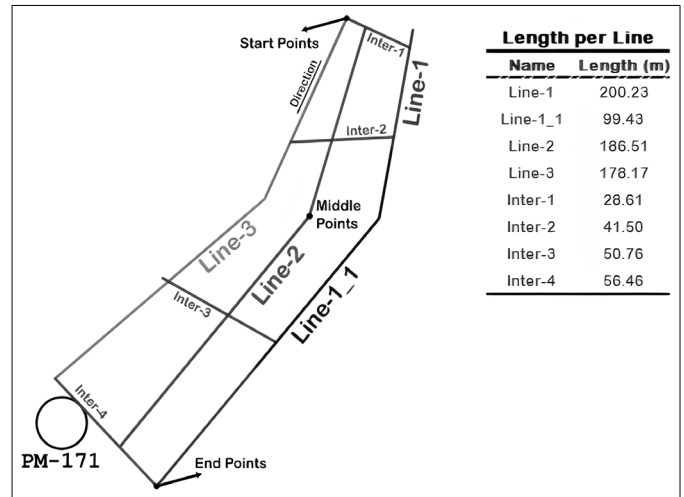

Figure 1. Field polygon of the 3 Electrical Resistivity Tomography profiles near borehole PM-171.
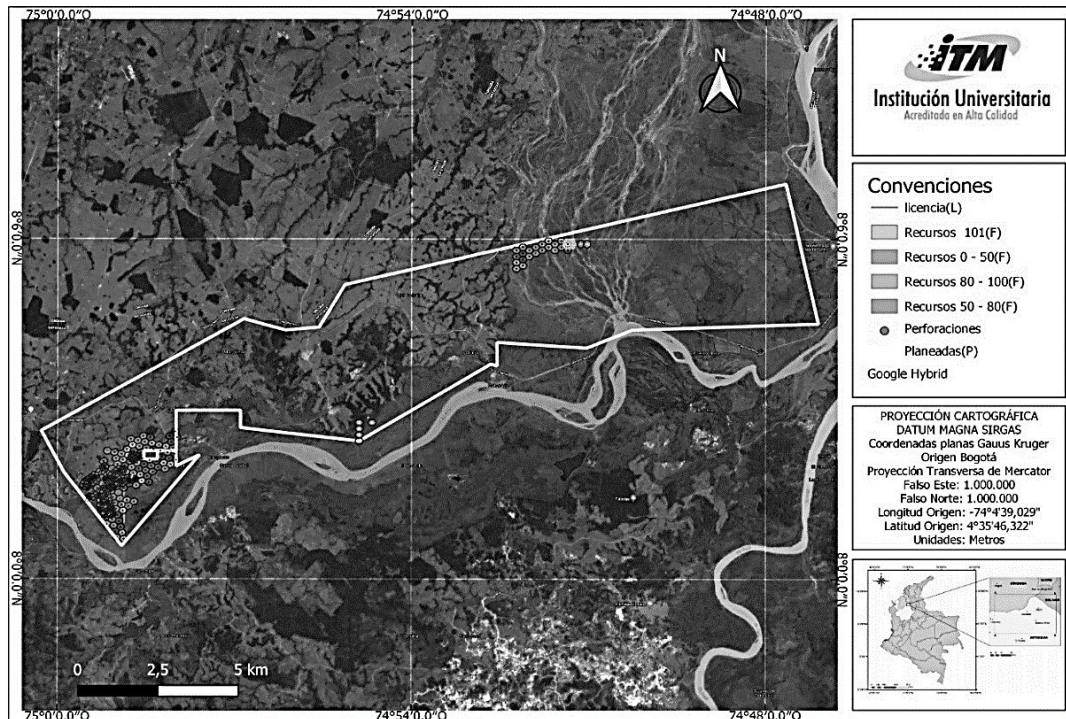Source: The authors.

Figure 2. Description of the mining license where the samples were taken.
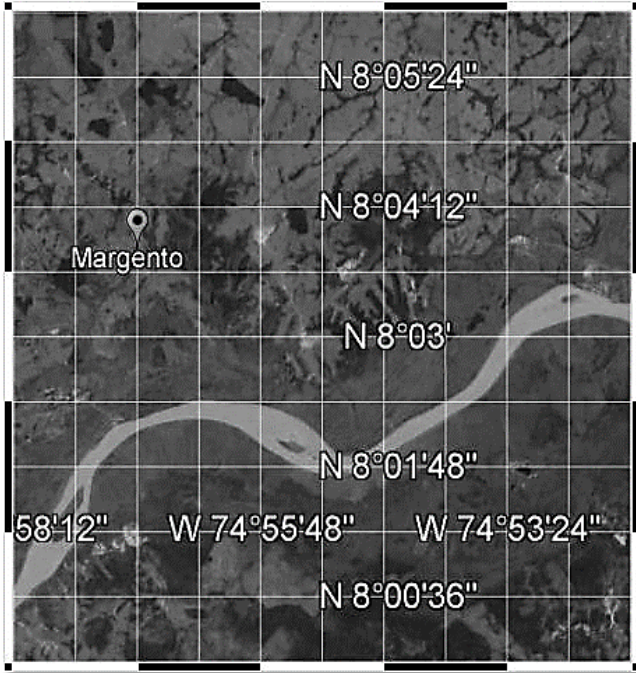Source: The authors.

Figure 3. Geographic coordinates for the hamlet of Margento.
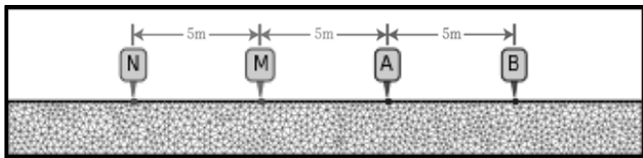Source: Google Earth Pro.

Figure 4. Inverted Dipole-Dipole Electrode Configuration, in which the power electrodes N-M and the current electrodes A-B can be observed in the order N-M-A-B, although they are also commonly ordered A-B-M-N.
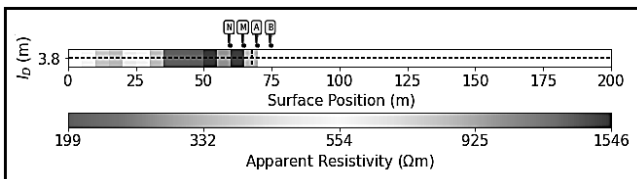Source: The authors and pyGIMLi.

Figure 5. Sampling at the first depth of investigation or depth I_D with a center spacing of 5 meters and taken approximately 67.5 meters from the point at which data collection commenced.
Source: The authors and pyGIMLi.

3. Processing

The pyGIMLi environment is an open-source, structured library that provides tools for modelling and inversion of electrical geophysical data [11]. It is structured because it depends on other libraries and a specific version of the programming language Python to function. It is supported by R programming languages for scientific computing [12].
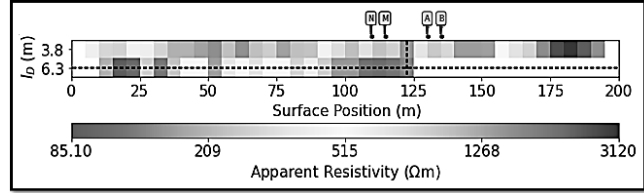

Figure 6. Sampling at the second depth of investigation or depth I_D with a center spacing of 15 meters and taken almost 125 meters from the point at which data collection commenced.
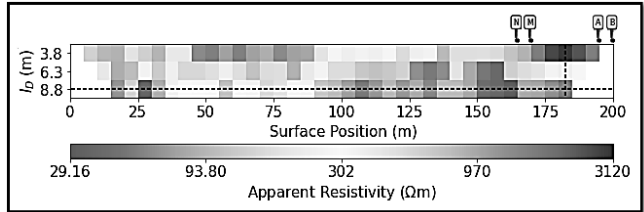Source: The authors and pyGIMLi.

Figure 7. Sampling at the end of the third depth of investigation or depth I_D with a center spacing of 25 meters and taken approximately 182.5 meters from point at which data collection commenced.
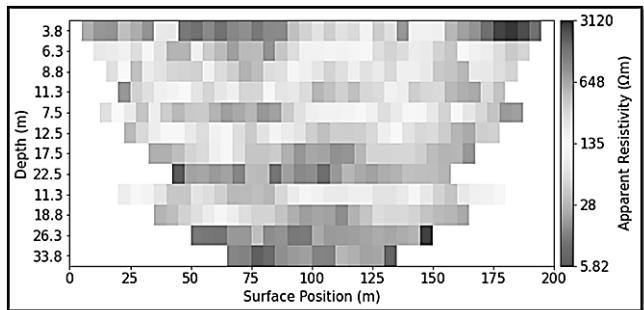Source: The authors and pyGIMLi.

Figure 8. Resistivity triangles of all the samples taken, showing a decrease in resistivity values as depth increases.
Source: The authors and pyGIMLi.

This library is particularly useful for manipulating RVector type variables, which are used to work with the system of linear equations on which pyGIMLi inversion is based (eq. 1-3) [13]:

$$\Phi = \Phi_d + \lambda\Phi_m \rightarrow \min \qquad (1)$$
$$\Phi_d = \|\mathbf{D}(\mathbf{d} - \mathbf{f}(\mathbf{m}))\|_2^2 \qquad (2)$$
$$\Phi_m = \|\mathbf{C}(\mathbf{m} - \mathbf{m}^0)\|_2^2 \qquad (3)$$

where:
- Φ represents the model solution of the Tikhonov regularization for data inversion [14,15].
- Φ_d is the residual norm.
- λ is the regularization parameter lambda.
- Φ_m is the solution norm.
- $\mathbf{D}$ is the diagonal matrix of the inverse of the
- relative measurement error vector err.
- $\mathbf{d}$ is the apparent logarithmic resistivity vector $log\ (rhoa)$.
- $\mathbf{m}$ is the logarithmic resistance vector $log\ (r)$.

- **f(m)** is an **m**-response model.
- **m**^{0} can be a model containing a-priori information, and **C** is the identity or diagonal weighting matrix.
- **m**^{0} can be a constant vector and use **C** to control the characteristics of the investment model.

3.1 Data import

pyGIMLi uses a structure called unified data format (UDF) that organizes the information contained in the geoelectrical data entered and ensures that all information is more transparent and transportable [16]. In other words, UDF makes it much easier to understand the information contained in the data delivered by the program and allows fully customized variability to be performed in functions like assignments, variable type transformation, copying, and rewriting.

Geoelectrical data taken with measurement equipment such as the ABEM Terrameter LS, AGI SuperSting, GeoSys, GeoTom, IRIS Instrument Syscal Pro, Lippmann [17-22] have different output formats, and other formats, such as res2dinv [23], also exist. The pyBERT library available in the Anaconda distribution [24] uses the lines of code in Algorithm 1 to convert these different data formats and line-3 into UDF.

3.2 Calculation of essential variables

For the basic inversion of geoelectric data in pyGIMLi, the following must be calculated:
- Relative measurement error err.
- Geometric factor k.
- Resistivity $rhoa$.

These must satisfy the required variables of the inversion model in eq. (1), since the samples give us the resistance r. This is achieved by using the lines of code from Algorithm 2 using the data already imported into the UDF.

3.3 Inversion process and parameters

With the essential variables now calculated, the ERT manager shown in Algorithm 3 performs the following set operations on the samples and parameters:

Algorithm 1.
Command for importing samples and other geoelectrical data output formats into the unified data format.

```
import pyber as pb
data = pb.import("linea-3.dat")
```

Source: Authors and pyGIMLi.

Algorithm 2.
Commands to calculate the essential variables of the pyGIMLi investment model.

```
import pygimli as pg
data['k'] = pg.physics.ert.createGeometricFactors(data)
data['rhoa'] = data['r']*data['k']
data['err'] = pg.physics.ert.estimateError(data)
```

Source: Authors and pyGIMLi.

- sr is defined as $True$ to calculate the primary potentials

that can be used in the secondary investment grid.
- $verbose$ is defined as $True$ to see the data processing flow (iterations) and the quality score of the inversion (chi-square $x2$). The latter is of vital importance since it is essential to obtain an $x2$ of between 1 and 5 [13] or if possible, of 1, to achieve a perfect fit.

Next, in the inversion, the following was defined:
- Regularization parameter $\lambda = 5$, corresponding to the λ of eq. (1).
- Maximum cell size $paraMaxCellSize = 1$.
- Maximum depth $paraDepth = 33.8$.
- Data boundary interpolation $paraBoundary = 0$.
- Robust data $robustData = True$,

and the ERT output was limited to the minimum and maximum apparent resistivity values shown in Fig. 8:
- $cMin = 5.82$.
- $cMax = 3120$.

4. Results

The application of Algorithm 4 returned the output parameters of the inversion shown in Table 1. Here, it is important to note that the value of x^2 is very close to 1, and this lends reliability and validity to the processed image and to the results for study. Additionally, the number of iterations is relatively low, and this indicates that the same machines and will easily obtain almost the same results. However, it is important not to disregard the fact that here,

Algorithm 3.
Commands for the inversion of ERT data with parameters defined for a x^2 between 1 and 5, and output of the resistivity map (ERT image).

```
import pygimli as pg
manager = pg.physics.ert.ERTManager(data, sr=True, verbose = True)

inversion = manager.invert(lam=5, paraMaxCellSize=1, paraDepth=33.8, paraBoundary=0, robustData=True)
manager.showResult()
```

Source: Authors and pyGIMLi.

Algorithm 4.
Open-source code in pyGIMLi for ERT processing of collected samples and applicable to other input data.

```
import pybert as pb
import pygimli as pg
data = pb.import("linea-3.dat")
data['k'] = pg.physics.ert.createGeometricFactors(data)
data['rhoa'] = data['r']*data['k']
data['err'] = pg.physics.ert.estimateError(data)
manager = pg.physics.ert.ERTManager(data, sr=True, verbose = True)

inversion = manager.invert(lam=5, paraMaxCellSize=1, paraDepth=33.8, paraBoundary=0, robustData=True)
manager.showResult(cMin=5.82, cMax=3120)
```

Source: Authors and pyGIMLi.

Table 1.
Sample inversion output parameters.

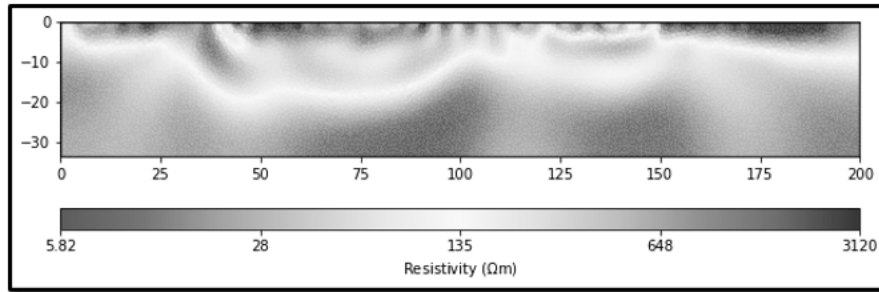| Iterations	dPhi	Chi-square
7	-3.13	1.1

Source: Authors and pyGIMLi.

Figure 9. ERT from the geoelectric data and the inversion process described in this paper.
Source: pyGIMLi.

The convergence criterion dPhi, while still a negative value, is close to 2%, and this is not desirable.

Fig. 9 shows the ERT that resulted from applying the whole processing scheme at once to the apparent resistivitydata of the Inverted Dipolo-Dipolo Array. Long zones of division between low and high resistivities can be observed, as well as a lateral interpolation very much in accordance with the distribution of the samples shown in Fig. 8.

This exercise determines that the structural construction produced the inversion of the pyGIMLi model provides results that enable the analysis and interpretation of the study zones.

It should be noted that the depth label is not automatically generated in the pyGIMLi image, so this must be done manually with reference to the plot commands of the matplotlib library.

5. Conclusions

The simultaneous sample processing technique gives an outstanding result in terms of educational benefit, since the process line can be applied constantly and repeatedly to the various samples to be taken. In this way, it bridges the gulf between knowledge and application, resulting in learning. The consolidation of these tools renders them exceptionally useful for problem solving, a skill of utmost importance in the 21st century and in the context of the fourth industrial revolution.

Literature review

Geoelectric processing techniques exist because of ill-posed problems (inverse problems) that can be applied to the field of geophysics through computerized tomography [25]. For many years now, mathematical models or numerical solutions have provided the main solution to these problems.

Tikhonov regularization is a model that was established by Andréi Nikoláievich Tíkhonov in his pioneering work of the 1960s, as mentioned by Benning and Burger [26]. It was adapted for the Gauss-Newton model scheme implemented by pyGIMLi [27]. However, Inman, Ryu, and Ward's resistivity inversion [28] was fundamental to the development of the quasi-Newton inversion system developed by Loke and Barker [29] which today has become the basis for a large amount of geoelectrical processing software used for many applications and research in mining and other fields.

Furthermore, artificial intelligence methods, such as deep learning, convolutional neuronal networks, and the fuzzy deep wavelet neural network [30-32], have been accruing importance as processing techniques in geoelectrics in recent years.

Acknowledgments

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B.A. Quiceno-Arenas, received a BSc. Eng. in Biomedical Engineering from the Instituto Tecnológico Metropolitano, Medellín, Colombia in 2022. He is currently studying for a master's degree in Industrial Automation and Control at the same university, with a special interest in data analysis for various types of phenomena.
ORCID: 0000-0002-6582-3767

J.G. Paniagua-Castrillón, has a BSc. Eng. in Mechanical Engineering from the Universidad de Antioquia, Medellín, Colombia. He received a PhD in Mathematical Engineering in 2018 and an MSc. in Engineering in 2014, both from Universidad EAFIT, Medellín, Colombia. He has taught Mathematics and Engineering at university level since 1998. In 2007 he joined the Faculty of Engineering at Instituto Tecnológico Metropolitano - ITM and is currently a full professor in the Electromechanical Engineering program. Professor Paniagua has experience in signal and image analysis and processing, and in mathematical modeling and simulation in geophysics. He is currently conducting research in the fields of mining and health, where he is working with simulation and mathematical modeling and artificial intelligence.
ORCID: 0000-0002-5829-5126

A.M. Muñoz-García, has a BSc. in Engineering Physics in 2008 and a MSc. in Engineering in 2010, from the Universidad Nacional de Colombia. He holds a PhD in Geosciences from the Universidad Nacional de Colombia. His research interests include petrophysics, rock physics, quantitative seismic analysis using machine learning, and electromagnetic techniques to study mineralization sedimentary deposits.
ORCID: 0000-0003-4136-2369

L.F. Duque-Gómez, received a BSc in 2003, and MSc in 2008, and a PhD in 2013, all in Physics, all ofthem from the Universidad de Antioquia, Medellín, Colombia. From 2003 to 2010, he worked for Universidad de Antioquia. Currently, he is a full professor in the Faculty of Exact and Applied Sciences at Instituto Tecnológico Metropolitano. His research interests include the simulation of nanoscopic systems, machine learning, and geophysics.
ORCID: 0000-0002-1039-3317

M.O. Bustamante-Rúa, has a BSc. Eng. in Mining and Metallurgy Engineering, from the Universidad Nacional de Colombia, an MSc. in Sciences of Engineering, with a mention of honor in Extractive Metallurgy and Mineralurgy, and a Dr. in Engineering Sciences, with a mention of honor in Extractive Metallurgy and Mining, both from the Universidad de Concepción, Chile. He is full professor at Universidad Nacional de Colombia, Medellín campus, and director and researcher at the Mineral Institute CIMEX.
ORCID: 0000-0002-1692-991X