Research Report

2D Inversion and Modeling Of
MT Anisotropic Data Using Clustering Technique

Integrated Master of Technology
IN
Applied Geophysics

BY
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UNDER THE GUIDANCE OF

Prof. Upendra K. Singh

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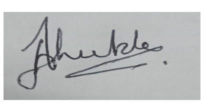
CERTIFICATE

This is to certify that Animesh Shukla, Admission No 18JE0114, has completed his Dissertation work entitled in partial fulfillment of the requirement for the award of Integrated Master of Technology in Applied Geophysics under the guidance of Prof. Upendra K. Singh in Indian Institute of Technology (Indian School of Mines), Dhanbad. This work has not been submitted elsewhere for any other degree or distinction.



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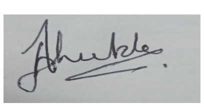

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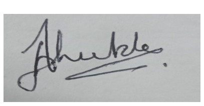

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TABLE OF CONTENTS

Abstract

This study shows the use of a fuzzy-c-means(FCM) clustering method, better an inverse two-dimensional (2D) resistivity model within a repetitive error minimization method. Fuzzy-constraint-inversion (FCI) and K-mean clustering are two techniques for Lp norm inversion of 2D DC (DC Anisotropic) resistance datasets that are represented throughout the Matlab platform. In this article we are comparing between FCM and K-mean clustering algorithm for optimizing the model post-inversion. In this paper, we use a pole–pole arrangement to compare a homogeneous model to a transversely-isotropic(i.e.,anisotropic) model with a tilted axis of symmetry. In this article data is we worked on modeling and Inversion of 2D DC resistivity data. The interpreter must give two more input parameters: (I) the quantity of geological blocks (i.e. clusters) in the system(model) , (II) the average resistivity values of every geological block (i.e.centroid values of the geological blocks). Experiments employing artificial(synthetic) and real data (i.e.,field data) of electrical-resistivity-tomography (MT) data demonstrate the efficiency of the provided technique. Both FCM and K-mean clustering tested on synthetic as well as on field data. For standard L1 and L2 norm minimization strategies, inversion results from the FCI algorithm are shown. After that we also looked up with K-mean clustering and compare both and we are finding better approach between them. When the method is given a large enough quantity of geologic blocks/units to work with, the FCI outperforms standard inversion algorithms in differentiating geologic units. Incorrect clustering knowledge will have an impact on the final resistivity-models, In the model, conducting geologic blocks/units are particularly important. We further show that FCI is effective whenever the MT data can be used to identify individual geological blocks/unit.

Chapter 1: Introduction

Direct current (DC) resistivity imaging or Magnetotellurics (MT) is a strong tool for obtaining a high-resolution subsurface resistivity image that has been used in a variety of applications,e.g., archeological exploration (Akca, 2016), demarcation(delineation) of aquifers/groundwater (Johnson et al.,2010), marine research (Loke and Lane, 2004 ; Rucker et al.,2011),etc. It gives data approximately, by introducing an electrical current into the earth's subsurface conductors as well as monitoring the current injected and capacity variations along with numerous places with the use of a variety of electrode arrangements. Electrodes could be buried or insMTed into boreholes. Inverse modeling is a mathematical structure for producing genuine subterranean resistivity models based on field data. Because the amount of MT-data measured is less than the quantity of units in the resistance membrane design, the inverse problem is confusing and insufficient in and of itself (Tarantola , 2005). Therefore, there are many underground resistivity models available, whose reaction can accommodate equally well to the measured resistivity dataset.

Over the last three decades, there has been much development in technology for interpreting DC resistance. The listing is large and only a couple of them are referenced in the article. e.g., 2D-interpretation, 3D-interpretation (Jackson et al., 2001 ;; Günther et al., 2006 ;; Pidlisecky et al., 2007), and 1D interpretation (Sharma , 2012). The above modeling techniques include an inversion strategy, storage, computational time, space, Visualization, and adaptation in different dimensions. After all, when it comes to reversing MT datasets, there are two primary challenges to consider. (1) The majority of inversion algorithms use L2 norm minimization to generate smooth resistivity images. (2) The restored resistivity value is lower/higher than the true underground resistivity as a result of the inversion algorithm. Due to the particular two major issues, the geological unit barrier of such an approach cannot be clearly distinguished due to the low contrast of the smoothed resistivity model. This makes it difficult to geologically interpret smooth resistivity patterns that are expected to have sharp boundaries. Yi et al. (2003) A technique for balancing active constraints was used to affect the extreme smoothing of the model. Other inverse techniques based on the L1 exist, criterion minimizes to create of mass structure in the ground (Farquharson and Oldenburg, 1998; Loki et al., 2003). Akca and Başokur (2010) have developed an approach to represent structure-based resistivity fractions by applying hybrid genetic algorithms. After all, they did not display their findings where there could be distinct lithological variations. Rücker (2011) incorporated previous information on structural stresses from the borehole and seismic data. Zhou et al. (2014) extracted the structural alignment of the geological zones and It was applied to the inversion with the help of a model covariance matrix.

The most frequent strategy for identifying the border between geologic units in the DC resistivity method is according to Laplacian and Gradient approaches (Sass , 2007; Hsu et al.,2010; Chambers et al., 2012). The gradient-based method determines the barrier of a resistive/conductive framework by identifying the max, the resistivity-model's first-derivatives, The Laplacian approach, on the other hand, looks for the curvature of the resistivity model. Wilkinson Et al. (2012) demonstrated that this technique may be inefficient because of the smoothness constraints in the DC resistivity inversion have a gradational aspect, as well as a limited resolution at depth due to the electrodes' increased inter-spatial distances. We frequently have some prior geological knowledge. Different geological units have a one-of-a-kind variety of resistivity values in a number of geological settings. As a result, such geological features can be classed based on their values of resistivity, with resistivity values that are statistically similar grouped together in a group or cluster (Doetsch et al., 2010 ; Ward et al., 2014 ; Ishola et al., 2015). Doetsch et al.(2010) and Ward et al.(2014) applied the clustering approach in post-inversion encoding to greatly enhance the pictures of resistivity. Infante et al. (2010), on the other hand, used geo-spectral and geophysical signs in the joint-inversion of seismic and electrical data to achieve a higher difference of 2 distinct geological blocks. Ishola Et al. (2015) used k-means clustering to join different configurations in their MT problem. A well-known hard clustering approach is K-Means method. Using the input data k, the number of clusters, it separates a set of n items into k clusters, with intra-cluster similarities high but inter-cluster similarities low. In this paper, we use the Lp norm to construct an inversion set of rules for the 2D-DC resistivity inverse issue. To enhance the understanding of underground resistivity patterns, we

employ fuzzy c-means(FCM) clustering approach and other clustering techniques directly in the inversion framework. We also show how clustering affects the inversion outcome. Electrical resistivity tomography (MT) is currently a standard technology for near-surface subsurface Investigation. There are two techniques to gather data from the Earth's surface: in two dimensions with co-linear electrode configurations, or employing estimated electrode configurations in three dimensions (e.g. Parkland Van , 1991 ; Ellis and Oldenburg , 1994 ; Loke and Barker,1995 1996). Crosshole DC electrical scanning, wherein electrodes are placed downhole in two or many horizontal spaced boreholes, moved throughout a depth range, is also common. Using comparable tomographic inversion processes for all of those who work with surface data, crosshole surveying can provide precise information on the fluctuation of electrical conductivity among boreholes at a better resolution than ground surveying. Almost all reported subsurface heterogeneity reconstructions assume that the medium is electrically isotropic. When it comes to stratified, fractured, and jointed rocks, such an idea is dubious, if not deadly. key issue is that anisotropic resistivity inversion is theoretically challenging and necessitates employment of the correct Fréchet derivatives. The following are some of the more significant causes that have played a role to the absence of anisotropic resistivity imaging: I)In what is generally an under-determined issue, Throughout the inverse, extra parameters have to be handled, II) In the original model, it is often not evident how to express the anisotropic form, and iii) Anisotropy cannot be identified from surface field observations whenever the axis of symmetry is vMTical. The advanced method is tested on-field and synthetic datasets respectively.

Chapter 2: Fundamental Concept of Geoelectrical Anisotropy

2.1 macro-anisotropy and Micro-anisotropy

Now here, discuss 2D DC **Anisotropic data,** Anisotropy describes a scenario in wherein surface resistivity (or conductivity), and thus voltage (or apparent resistivity) measurement, varies with measurement direction. Such dependence on direction is typical in materials with distinct lineation or platy fabric, such as shale, slate, and clay. It can also be found in some minerals, and known as **micro-anisotropy** or intrinsic anisotropy, and it is determined by material's texture or crystal symmetry. On a macroscopic scale, anisotropy can emerge when a chain of bands/layers of different isotropic materials operate as if they were a single anisotropic block. This form of structural anisotropy can also be caused by fracture, jointing, and rock cleavage, If this is the case, the "layers" would get different resistivities (joint fill and rock). Pseudo-anisotropy occurs whenever the width of a single or isolated isotropic unit or band is small as compared towards the electrode separation employed in the study. Generally, a second rank tensor must be used to characterize resistivity, and the tensor ellipsoid must be used to describe anisotropy (Greenhalgh et al., 2009b). However, for the time being, it will work with the basic model of a transversely isotropic media. Within a specific plane, the resistivity is constant (isotropic) in this model (e.g., fracture plane, stratification plane) and that is widely used Outside of that plane, however, it varies in every other direction. When measured perpendicular to this plane (referred to as transverse resistivity ρ), resistivity levels are prone

2.2 Anisotropy's influence on field measurements

When anisotropy happens withinside the surface however is neglected, the actual ground resistivities and geology shape derived from measured obvious resistivity can be erroneous. Matias and Habberjam (1986), Habberjam (1972, 1975), and Matias (1988) are papers that discuss the Anisotropy's effect on resistivity of surface evaluation (2002). When the TI medium's axis of symmetry is vMTical, as it is for parallel(horizontal) bedding, Standard resistivity measurements made on the surface are constant in all horizontal directions. When such anisotropy is present, the estimated depth depends on the coefficient of λ.

Now consider a situation in which the TI medium's axis of symmetry is sort of horizontal (e.g., cracks or steeply sinking beds). The resistivity measured by the electrodes placed in one direction is different from that recorded with similar electrode array orientation in a different path(direction) in this scenario. If there's no overburden, it's paradoxical to measure apparent(obvious) resistivity for steeply sloping beds. Since current flows down the routes with least resistance, one may anticipate the recorded resistivity (similar genuine resistivity) to be the lowest-parallel to hit. In fact, due to higher current density parallel to the survey line, along the strike, the measured resistivity is greater. the apparent(obvious) resistivity computation accepts a uniform current thickness in the three bearings. The observed potential difference for a given current source is larger when the when the current density is higher than on uniform isotropic surface(ground), follow in greater apparent resistivity. The apparent resistivity is, as a matter of fact, equivalent to ρ . In contrast, the apparent resistivity assessed 90 degrees to the strike is equivalent to the genuine longitudinal resistivity, not the transverse resistivity ρ . This is called the paradox of anisotropy.

Chapter 3: Methodology

3.1 Two-dimensional forward modeling and sensitivity computation

Forward modeling is a critical component of any inversion approach. The following elliptic partial differential equation of Poisson type (Günther , 2004) is solved in 2D DC (Anisotropic/Isotropic) resistivity forward modeling to compute the potential distribution V (x,y,z) over a 2D conductivity structure (σ) due to a current source (I)

$$-\nabla[\boldsymbol{\sigma}(x,z)\nabla \boldsymbol{V}(x,y,z)] = \boldsymbol{I}(x,y,z).$$

(1) There are a few mathematical ways to deal with tackling Equation 1: finite element method (Coggon ,1971 , Rijo ,1977 , Queralt et al., 1991 ; Xu et al., 2000), finite difference method (Mufti , 1976i, Dey and Morrison , 1979), finite volume method (Mufti , 1976, Dey and Morrison , 1979), finite (Pidlisecky et al., 2008). In this paper, we apply the limited component strategy to settle equation 1 to compute the potential difference, and then we use the general methodology of Marescot et al. to determine the apparent resistivity (2006). Using Edwards' technique, the apparent resistivity values are afterwards turned into pseudo depth sections (1977). The discrete solution to equation 1 is as follows:

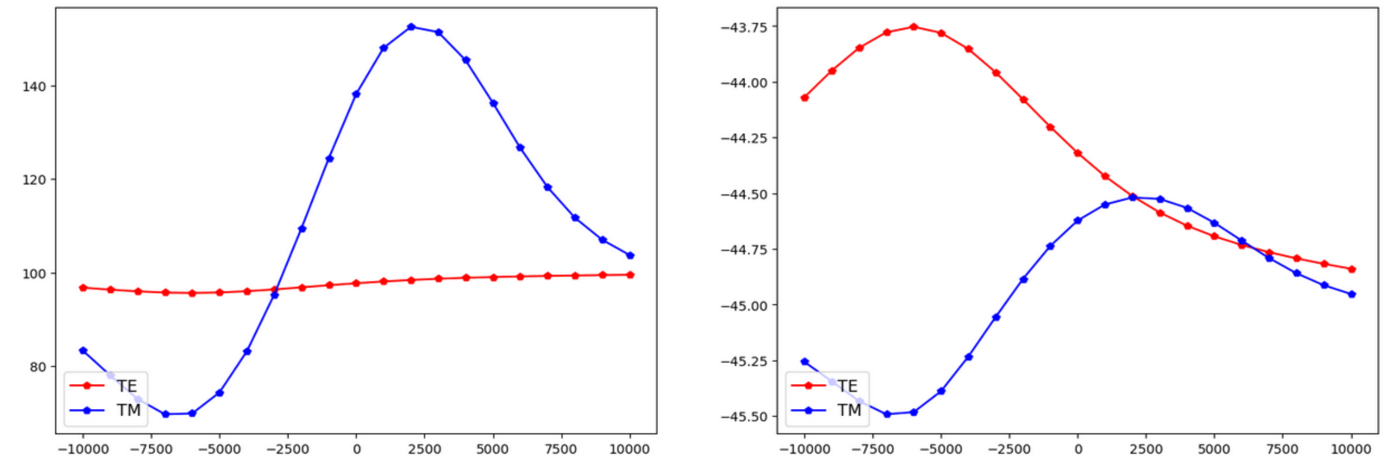

Figure1: Transverse Electric and Transverse Magnetic plotting of synthetic data points.

3.2 Fuzzy clustering

The clustering technique is to place the data in a group of identical objects. Every cluster contains elements that are similar to each other and different from the items in the other groups. Multiple clustering approaches are accessible in the article (e.g., Macqueen , 1967; Bezdek , 1981). Fuzzy c-means is a clustering approach, allows a single piece of data can be assigned to 2 or many groups. Using fuzzy memberships.

the FCM clustering approach gives blocks to groups (clusters). Denotes the M number of blocks' resistivity that will be divided in to C number of geological blocks (i.e. the total quantity of clusters). To do so, we can iteratively reduce the below the function of the aim. (Bezdek , 1981)

$$\phi^c = \sum_{k=1}^{M} \sum_{i=1}^{c} \mu_{ik}^q \left\| m_k - u_i \right\|_2^2 , \qquad (3)$$

2

by the weighting exponent q and || || , respectively. Wade et al. (2014) observed that 2

fcm clustering does not produce distinct results when used repeatedly and proposed a method termed guided fcm clustering. Using kernel density estimation, they generated preset cluster centers using observed DC data sets (Botev et al., 2010). As a result, in our fcm clustering formulation, we include a priori cluster centers vi (Sun and Li, 2015).

$$\phi^c = \sum_{k=1}^{M} \sum_{i=1}^{c} \mu_{ik}^q \left\| m_k - u_i \right\|_2^2 + \sum_{i=1}^{c} w_i^c \left\| u_i - v_i \right\|_2^2,$$

(4) where W referred as weight assigned to the a priori(presumptive) cluster center v. When the previous equation is written in matrix form, the solution is

$$\phi^c = \sum_{i=1}^{c} \boldsymbol{\mu}_i^q \left\| \boldsymbol{m} - u_i \right\|_2^2 + \sum_{i=1}^{c} w_i^c \left\| u_i - v_i \right\|_2^2.$$

(5) 15

To find the optimal cluster centers value and Each membership value (μ), we undMTake repetitive minimization of the function of the objective in equation 5 . The cluster facilities are iteratively up to date primarily based totally on the brand-new club data (μ). This method is repeated till the termination standards (ε) are met. In this study, a value of 2 is allocated to the weighting exponent q. The recursive minimization of the fuzzy c-means, function of the objective is presented here from a well-known Bezdek method (1981)

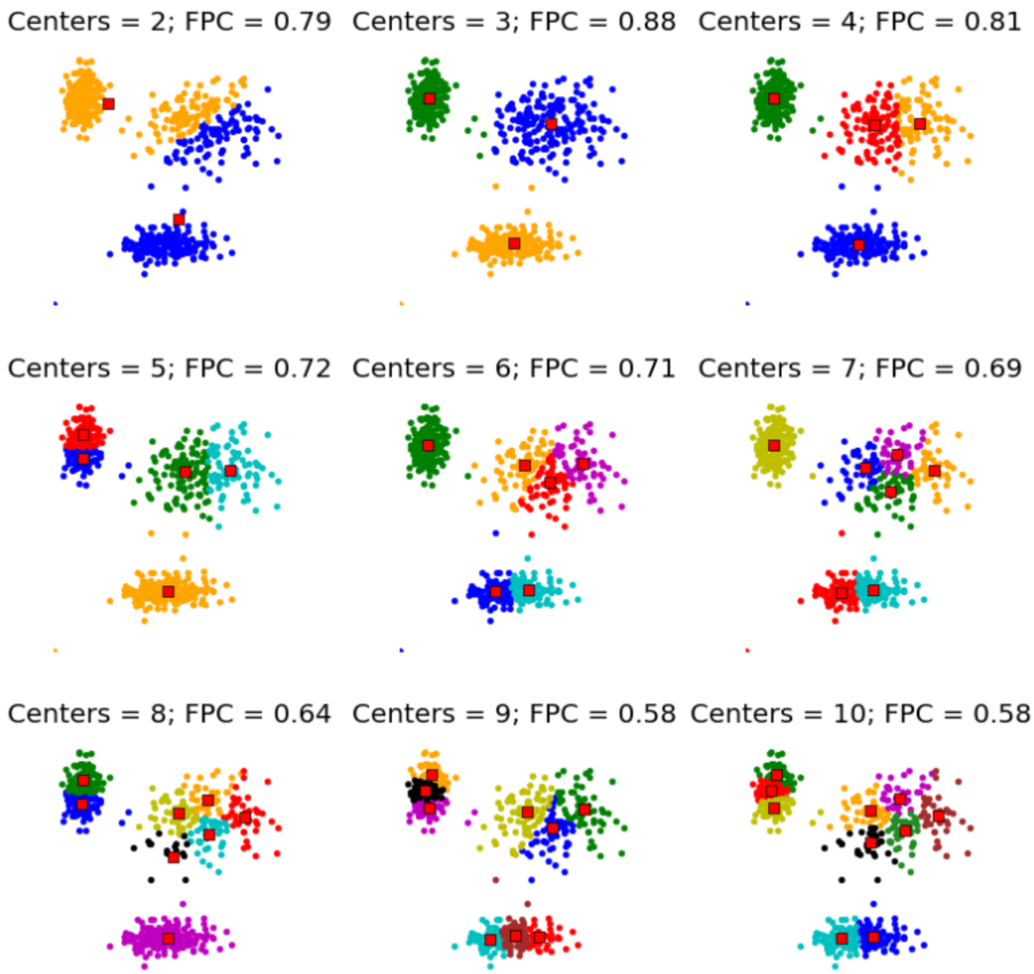

Figure2: Explains the variation in result with increasing number of center of the clusters, centers vary from 1 to 10 similarly FPC (Fuzzy Partition coefficient) gives the result which will be the best number of the centers.

Chapter 4: Result and discussion

Synthetic apparent resistivity data to demonstrate the effectiveness of fuzzy constrained inversion Generated for pole-pole type electrode configurations in 2D models. Resistivity inversion based on L1 and L2 criteria of the artificial data was carried out with the basic inverse method discussed in the inversion section. The same data is then invMTed using the suggested fuzzy constrained inversion.

4.1 Synthetic Model inversion

Figure 1a illustrates this, we tested artificial model inversion utilizing a two-block model with a dramatic resistivity contrast (Boonchai Suk et al., 2008). Two blocks with a resistivity of 100 Ωm and 1 Ωm were placed side by side in a uniform half-space with a resistivity of 10 Ωm. The reaction of model was determined for the dipole-dipole configuration design. The synthetic data set was given 5% Gaussian noise (Figure 1b). The entire model area has been discretized into 58 x19 blocks. The model is made up of three geological block with average resistivity values of one (1), ten (10), and one hundred (100) Ω m (histogram chart in Figure 1a). If the resistivity of geological blocks is recognized via estimation of rock samples or even other geophysical investigations (e.g.,boreholes), using the given fuzzy constrained inversion (FCI), we can more exactly reconstruct the resistivity model (FCI). For k=1 to 3 , we assign c to 3 and k to [1 , 10 , and 100] m. Figures 1c and 1d illustrate the resistivity model recovered from simple inversion with no constraints on fuzzy clustering for L2 and L1 norms, respectively. The restored resistivity models by FCI employing L2 are shown in Figures 1e and 1f. The regenerated resistivity models via fuzzy constrained inversion (FCI) employing L2 and L1 norms are displayed in Figures 1and1, respectively. The boundaries of the blocks are clearly visible in Figures 1e and 1f acquired through FCI as opposed to Figures 1c and 1d obtained by basic inversion. The efficiency of the given FCI is demonstrated in both of the preceding artificial cases. We want to underline that the FCI inversion through the L1 norm (Figures 1f) restores boundaries to the actual model more precisely than the FCI inversion through the L2 norm (Figures 1e), especially in the vMTical direction. The L2 Norm FCI model's resistivity limitations are 24 Lower than the L1 norm FCI model's resistivity ranges. The resistivity limits in L2 Norm FCI model are less than the resistivity ranges in the L1 Norm FCI model. This explains why, when compared to L2 norm FCI, L1 norm FCI required less iterations to retrieve the actual model (Figure 2)

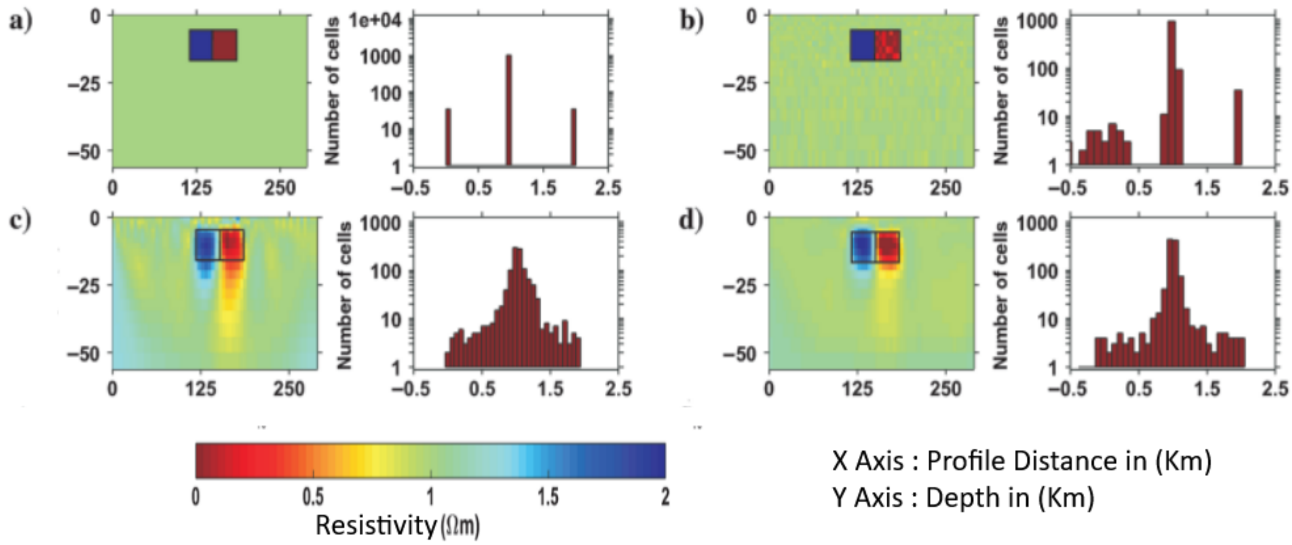

Figure 1. Inversion results for two blocks models with high resistivity contrasts. (a) True resistivities of the model, and (b) same model with 5 % Gaussian noise. Models obtained after inversion of the synthetic data are shown in (c) using L2 norm, (d) using L1 norm, (e) using FCI with L2 norm and (f) using FCI with L1 norm. The second and fourth columns represent histogram plots of corresponding resistivity models to their left.

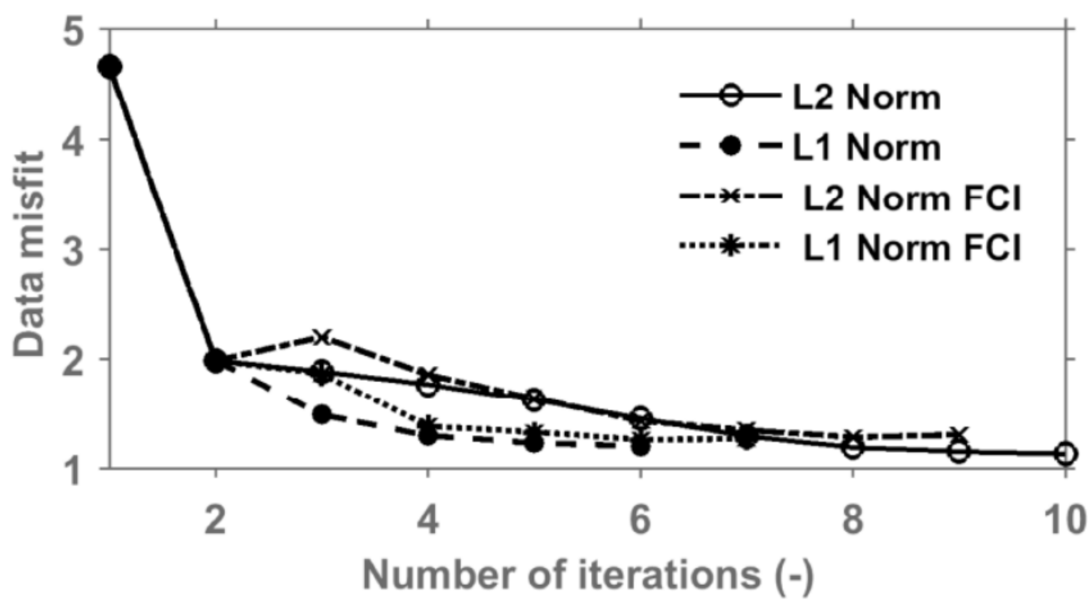

Figure 2: During the iterations for Inversion, the data misfit pattern converged.

4.3 Field Model using FCI

To test the effectiveness of the suggested inversion technique on field data, we inverted 2D MT profile anisotropy data from Solbergietiali Published .'s work (2016). The data were gathered using a gradient array with 5 m spacing from a quick-clay landslide area at Esp , Trondheim , Norway. Several geophysical and geotechnical surveys were previously conducted on this site following a landslide in 2012. (Solberg et al., 2015; Baranwal et al., 2015 , 2017). As illustrated in Figure 3a, Solberg et al. (2016) identified

four geologic units along this 2D MT profile: (1) unleashed clay deposition (1–10 m), (2) leached clay deposition or potential fast clay (10–100 m), (3) dry crust clay deposits and coarse sediments (>100 m), and (4) bedrock (> 500 m). Figure 3b depicts a revised inversed resistivity model based on the same fundamental L1 Norm (as mentioned in inversion chapter). Figures 3a and 3b show that the borders between geologic units are not very well differentiated or delineated. Known to that area for getting information for fuzzy constraint inversion. In fuzzy constraint Inversion, priori information is required so we had gathered some information about that area from several articles (e.g., Hundal , 2014 ; Montafia , 2013). In this area they performed RCPTU for measurement of subsurface resistivity at two different places. Here RCPTU stands for Resistivity cone penetration test unit. RCPTU is a small-scale 4-electrode sounding method used to find electrical resistivity in cohesive soils by pressing the unit vertically (NIFS , 2014). The differences in resistivity at these two places are identical, as illustrated in Figure 4b. The histogram distribution of resistivity recorded at two locations is displayed in Figure 4c (y-axis at left). A kernel density estimate function (Botev et al., 2010) is used to determine the distinct resistivity barriers existing at sites B1 and B2, and the resultant figure is displayed in Figure 4c (y-axis at right). As a result, we had more a priori knowledge added in the fuzzy constrained inversion of the 2D MT data.

We used two clustering information to invMT observed 2D MT data (Anisotropy), (1) Two geological unit is here (considered 2 body problem), (2) and their mean resistivity value. Number of cluster we had used 3. Figure 5a depicts the resultant resistivity model after L1 norm fuzzy constrained inversion. According to the histogram chart Figure 5b, the L1 Norm FCI inversed resistivity model Figure 5a displays more distinct border differences than fig 3. After that worked with L2 norm Figure 6a and their corresponding histogram chart shown in Figure 6b. According to the FCI section, geologic blocks could also be individually identified by allocating every unit to the cluster with the greatest membership values (i.e., defuzzification), With each iteration, after calculating for model updates. Figure 7a and 7b shows the convergence of FCI with L1 norm and L2 norm. FCI with L1 norm converges faster than FCI with L2 norm. Figure 5d depicts the calculated apparent resistivity pseudosection for the resistivity model shown in Figure 5a following fuzzy L1 norm inversion . Following fuzzy L2 norm inversion,

illustrates the estimated apparent resistivity pseudo-section for the resistivity model illustrated in Figure 6a.As a result, if the user provides the correct amount of geologic units, FCI is incredibly effective at deciphering various geologic items in the modeling area. It is vital to note that we have a basic concept of the quantity of various geological blocks available in the survey area as a prior knowledge for field data interpretation. Nevertheless, there may be geologic instances when we do not have such prior knowledge. Clustering findings were statistically analyzed, one can determine the ideal number of cluster centers in various geologic conditions (Milligan and Cooper, 1985; Halkidi et al. 2001). After comparing the Figure 5a (Fuzzy with L1 norm) and 6a (Fuzzy with L2 norm), we found that 5a has sharper boundary as compared to 6a and therefore we cant define the boundary in 6a like 5a. If you look Figure 5c and Figure 6c we found that Fuzzy with L2 not worked properly some blurriness is present. Figure 5c and Figure 6c represent the Horizontal and vMTical apparent Resistivity.

Chapter 5: Conclusion

5.1 Conclusion

Any clustering-algorithm used, post-inversion step may differ from the True model obtained by inverting recorded values. As a result, a technique for defining geologic units from geoelectrical resistivity models is described that incorporates a clustering mechanism within the inversion algorithm. The method is based on applying fuzzy c-means and K-means clustering to the ERT data's 2D inversion (Anisotropy). FCI satisfies two requirements: (1) to achieve a resistivity model with a response that minimizes the data misfit function (2) Additional a priori parametric information will be used to steer the retrieved resistivity model.In k-means (which is not fuzzy), each point belongs to a centroid, whereas in fuzzy c-means, each point can belong to two centroids of varying quality. We show, using synthetic example, In models produced from classic L1 and L2 norm inversions, the boundaries among geologic blocks are less visible. Nevertheless, if FCI is given the correct quantity of the geologic block, the reported FCI can be used to distinguish between two or more geologic blocks/units. In case of K-mean clustering we cant able to distinguish the geological unit because of their weight and its behave like hard clustering. We additionally note as L1 norm Fuzzy constraint inversion resistivity imaging describe resistivity borders greater than L2 norm Fuzzy constraint inversion resistivity imaging. Inversion for artificial models likewise shows that conductive geological units are more affected by inaccurate clustering knowledge than resistive geological blocks. The L1 norm converges more quickly, as evidenced by artificial(synthetic) instances. We also found that FCI with L1 gives more robust model as compared to FCI with L2. Critical inputs are a preexisting knowledge of the correct quantity of cluster centers and the true values of these centroids. The right number of centroids and the corresponding output of these centroids are both essential factors for an effective FCI, but the correct number of centroids seems to be more significant. The usefulness from given FCI in distinguishing the borders of likely fast clay regions by other geologic blocks is demonstrated using field data . The FCI resistivity model adequately includes parametric data from previous geophysical-and

-geotechnical studies while preserving identical degree of fit among visible and calculated data, shown by the generic inversion. In K-mean clustering there is effect of L1 norm and L2 norm, we got the same result for both. Here I am concluding my all point that FCM is better than K-mean clustering for 2D DC anisotropic data.

5.2 Future Planning

These algorithms, as is evident, show promising results and maybe applied in various domains of geophysics. We can apply the data in facies classification in seismic as well as well log data by taking advantage of the fact that the rocks with similar properties will have similar signatures in the geophysical surveys. We can also extend this work to inversion of other datasets as well such as seismic, MT, well logs and also focus on 3D anisotropy by performing inversions on 3D surveys

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