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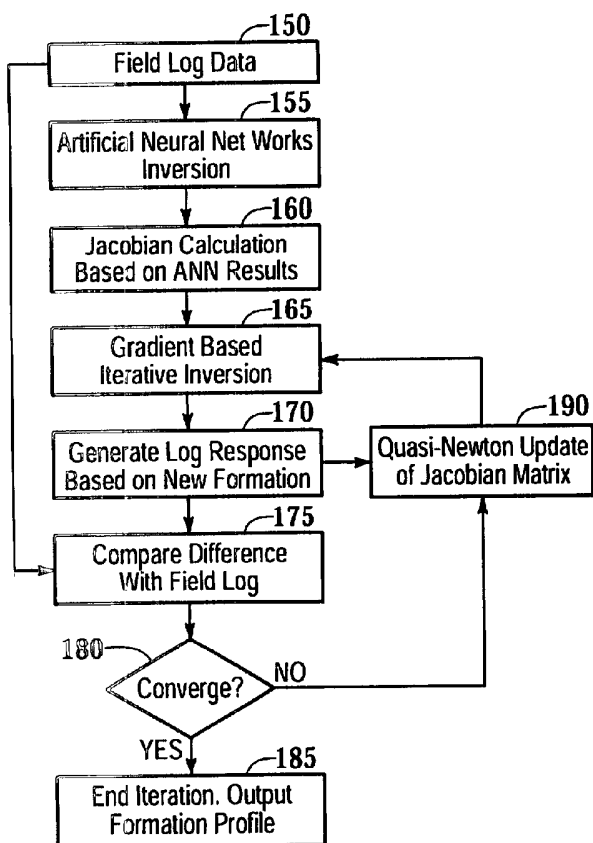
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(54) Title: METHOD FOR DETERMINING PARAMETERS OF EARTH FORMATIONS SURROUNDING A WELL BORE USING NEURAL NETWORK INVERSION



(57) Abstract: A method for determining a formation profile 185 surrounding as well is used to establish a first formation profile 185 using a neural network inversion method 155. A synthetic log 170 is generated from the first formation profile and if the synthetic log converges 180 with a real log 150, the formation profile parameters associated with the synthetic log are output 185. Otherwise, the first formation profile is modified and a new synthetic log 170 is generated.

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**METHOD FOR DETERMINING PARAMETERS OF
EARTH FORMATIONS SURROUNDING A WELL BORE
USING NEURAL NETWORK INVERSION**

5 CROSS REFERENCE TO EARLIER APPLICATIONS

This patent application claims priority from United States Patent Application No. 10/208,384, filed on July 29, 2002, entitled "Method for Determining Parameters of Earth Formations Surrounding a Well Bore Using
10 Neural Network Inversion".

BACKGROUND OF THE INVENTION

Technical Field of the Invention

The present invention relates to well logging, and more particularly, to
15 a method for determining formation parameters around a well bore using neural network inversion.

Description of Related Art

Modern petroleum drilling and production operations demand a great quantity of information relating to parameters and conditions downhole. Such
20 information typically includes characteristics of the earth formations traversed by the wellbore, in addition to data relating to the size and configuration of the borehole itself. Oil well logging has been known in the industry for many years as a technique for providing information to a formation evaluation professional or driller regarding the particular earth formation being drilled.
25 The collection of information relating to conditions downhole, which commonly is referred to as "logging," can be performed by several methods. These methods include measurement while drilling, MWD, and logging while drilling, LWD, in which a logging tool is carried on a drill string during the drilling process. The methods also include wireline logging.

In conventional oil well wireline logging, a probe or "sonde" is lowered into the borehole after some or all of the well has been drilled, and is used to determine certain characteristics of the formations traversed by the borehole. The sonde may include one or more sensors to measure parameters downhole and typically is constructed as a hermetically sealed cylinder for housing the sensors, which hangs at the end of a long cable or "wireline." The cable or wireline provides mechanical support to the sonde and also provides electrical connections between the sensors and associated instrumentation within the sonde, and electrical equipment located at the surface of the well. Normally, the cable supplies operating power to the sonde and is used as an electrical conductor to transmit information signals from the sonde to the surface. In accordance with conventional techniques, various parameters of the earth's formations are measured and correlated with the position of the sonde in the borehole as the sonde is pulled uphole.

A chart or plot of an earth parameter or of a logging tool signal versus the position or depth in the borehole is called a "log." The depth may be the distance from the surface of the earth to the location of the tool in the borehole or may be true depth, which is the same only for a perfectly vertical straight borehole. The log of the tool signal or raw data often does not provide a clear representation of the earth parameter which the formation evaluation professional or driller needs to know. The tool signal must usually be processed to produce a log which more clearly represents a desired parameter. The log is normally first created in digital form by a computer and stored in computer memory, on tape, disk, etc. and may be displayed on a computer screen or printed in hard copy form.

The sensors used in a wireline sonde usually include a source device for transmitting energy into the formation, and one or more receivers for detecting the energy reflected from the formation. Various sensors have been used to determine particular characteristics of the formation, including nuclear sensors, acoustic sensors, and electrical sensors. See generally J. Lab, A Practical Introduction to Borehole Geophysics (Society of Exploration

Geophysicists 1986); D.R. Skinner, Introduction to Petroleum Production, Volume 1, at 54-63 (Gulf Publishing Co. 1981).

For a formation to contain petroleum, and for the formation to permit the petroleum to flow through it, the rock comprising the formation must have certain well-known physical characteristics. One characteristic is that the formation has a certain range of measurable resistivity (or conductivity), which in many cases can be determined by inducing an alternating electromagnetic field into the formation by a transmitter coil arrangement. The electromagnetic field induces alternating electric (or eddy) currents in the formation in paths that are substantially coaxial with the transmitter. These currents in turn create a secondary electromagnetic field in the medium, inducing an alternating voltage at the receiver coil. If the current in the transmitter coil is kept constant, the eddy current intensity is generally proportional to the conductivity of the formation. Consequently, the conductivity of the formation determines the intensity of the secondary electromagnetic field, and thus, the amplitude of the voltage at the receiver coil. See generally, James R. Jordan, et al., Well Logging II -- Electric And Acoustic Logging, SPE Monograph Series, Volume 10, at 71-87 (1986).

An exemplary induction tool is shown in the prior art drawing of Figure 1, in which one or more transmitters (T) and a plurality of receivers (R_i) are shown in a logging sonde. Each transmitter or receiver may be a set of coils, with modern array induction tools having several receivers, e.g. R₁, R₂, R₃, and R₄, of increasing transmitter-to-receiver spacing to measure progressively deeper into the formation.

In a conventional induction tool such as that shown in Figure 1, the coils are wound coaxially around a cylindrical mandrel. Both transmitter coils and receiver coils are solenoidal, and are wound coaxial with the mandrel. Such coils would therefore be aligned with the principal axis of the logging tool, which is normally also the central axis of the borehole and is usually referred to as the z-axis. That is, the magnetic moments of the coils are aligned with the axis of the mandrel on which they are wound. The number, position, and

numbers of turns of the coils are arranged to null the signal in a vacuum due to the mutual inductance of transmitters and receivers.

During operation, an oscillator supplies alternating current to the transmitter coil or coils, thereby inducing current in the receiver coil or coils.

5 The voltage of the current induced in the receiver coils results from the sum of all eddy currents induced in the surrounding formations by the transmitter coils. Phase sensitive electronics measure the receiver voltage that is in-phase with the transmitter current divided by magnitude of the transmitter current. When normalized with the proper scale factor, this provides signals
10 representing the apparent conductivity of that part of the formation through which the transmitted signal passed. The out-of-phase, or quadrature, component can also be useful because of its sensitivity to skin effect although it is less stable and is adversely affected by contrasts in the magnetic permeability.

15 As noted, the induced eddy currents tend to flow in circular paths that are coaxial with the transmitter coil. As shown in Figure 1, for a vertical borehole traversing horizontal formations, there is a general symmetry for the induced current around the logging tool. In this ideal situation, each line of current flow remains in the same formation along its entire flow path, and
20 never crosses a bed boundary.

In many situations, as shown for example in Figure 2, the wellbore is not vertical and the bed boundaries are not horizontal. The well bore in Figure 2 is shown with an inclination angle Θ measured relative to true vertical. A bed boundary between formations is shown with a dip angle α .
25 The inclined wellbore strikes the dipping bed at an angle β . As a result, the induced eddy currents flow through more than one media, encountering formations with different resistive properties. The resulting logs are distorted, especially as the dip angle α of the bed boundaries increases. If the logging tool traverses a thin bed, the problem becomes even more exaggerated.

30 As shown in the graph of Figure 3A, an induction sonde traversing a dipping bed produces a log with distortions normally referred to as "horns".

The more severe the dip angle, the less accurate is the measurement with depth. Figure 3A represents a computer simulation of a log that would be generated during logging of a ten-foot thick bed (in actual depth), with different plots for different dip angles. Figure 3B shows a computer simulation of a log which would be generated if the thickness of the bed were true vertical depth, with different plots for different dip angles. As is evident from these simulated logs, as the dip angle increases, the accuracy and meaningfulness of the log decreases. In instances of high dip angles, the plots become virtually meaningless in the vicinity of the bed boundaries.

Figures 3A and 3B also illustrate that even for a vertical well traversing horizontal formations, the actual electrical signal or data produced by an induction logging tool is quite different from an exact plot of formation resistivities. In these figures the desired representations of formation resistivity are the dashed line square wave shapes 10 and 20. The actual resistivity within a layer is generally uniform so that there are abrupt changes in resistivity at the interfaces between layers. However, logging tools have limited resolution and do not directly measure these abrupt changes. When the transmitter coil T in Figure 1 is near an interface, as illustrated, its transmitted signal is split between layers of differing resistivity. As a result, the raw data or signal from the logging tool is a composite or average of the actual values of the adjacent layers. This effect is referred to as the shoulder effect. Even in the 0° case shown in the Figure 3A and 3B, where the tool is vertical and the formation is horizontal, the measured data is quite different from the desired representation of resistivity. As the dip increases, the effect is increased.

Much work has been done on methods and equipment for processing logging tool data or signals to produce an accurate representation of formation parameters. This data processing process is commonly called inversion. Inversion is usually carried out in some type of computer. In the prior art system of Figure 1, a block labeled "computing module" may perform some type of inversion process. The methods currently available to perform

this processing are iterative in nature. The standard iterative methods have the disadvantage of being computationally intensive. As a result, the inversion must normally be carried out at computing centers using relatively large computers, which can deliver results of the inversion in a reasonable
5 amount of time, and normally cannot be performed in computers suitable for use at the well site.

An alternative processing method is the deconvolution method. This method is very fast and can be implemented at the well site, for example in the computing module of Figure 1. However, this method is based on linear
10 filter theory, which is an approximation that is not always accurate. In deviated boreholes, the nonlinearity of the tool response becomes manifest, making the problem hard for the deconvolution method to handle. The deconvolution methods do not generate actual representations of the formation parameters, so they cannot be properly called inversion methods.

15 Early attempts to solve the inversion of log data problem used the parametric inversion method. This method is an iterative method that uses a forward solver and criteria, such as the least square inversion, to determine the best fit for the parameters of a predefined formation, usually a model with a step profile. However, if the actual formation does not conform to the
20 predefined model, the output parameters determined by this method can be very far from the actual parameters of the formation. This is a consequence of the ill posed nature of the inversion problem which makes it highly non-trivial.

A more current method for inversion of resistivity log data is the
25 Maximum Entropy Method, MEM. In this iterative method, a test or proposed formation model is modified to maximize the entropy functional, which depends on the parameters of the formation. This method does not use a predefined formation and produces solutions of better quality. It is more efficient than the parametric approaches, but is still computationally intensive.
30 It can be applied to any type of tool for which a forward solver is available. An example of the MEM method is disclosed in US Patent 5,210,691 entitled

"Method and Apparatus for Producing a More Accurate Resistivity Log from Data Recorded by an Induction Sonde in a Borehole."

Induction logging plays a crucial role in formation evaluation for the exploration of hydrocarbons. It is primarily used to delineate between hydrocarbon-bearing zones and non-hydrocarbon zones. Formation resistivity derived from induction tools is used to estimate oil-in-place in the hydrocarbon-bearing zones. Unfortunately, the interpretation of induction logging data is made difficult by the limits of basic physics of induction tools. Specifically: i) induction tools investigate large volumes surrounding the borehole, ii) induction tool response depends nonlinearly on formation conductivity, and iii) modern array induction tools such as Halliburton's HRAI are highly complex with an assortment of transmitters and receivers that have different characteristics. As a result, the apparent resistivity profile generated by an induction tool is far from the true formation resistivity profile.

Since the introduction of the first induction tool, efforts have been made in attempt to correct the adverse environmental effects such as shoulder bed effect, skin effect, etc., with the aim of enhancing its resolution. An approach that is frequently used by log analyst to interpret induction logging data is the familiar trial-and-error method, whereby a log analyst starts with an assumed formation resistivity profile to generate a model response using predicative forward modeling. The obvious drawbacks of this approach are that it is time consuming and the possible bias introduced by even the most experienced interpreter.

Traditionally, inverse filters were used to deconvolve induction logs. This is based on the recognition that induction log can be approximated as a convolution of formation conductivity and a canonical tool response function. Inverse filters have been used to deconvolve the raw logging data. This operation is normally carried out at the well site on the logging truck. Although this technique has been widely used for years, it is known to introduce unwanted spurious effects.

An alternative approach to enhance induction tool resolution is to carry out a full inversion. Least-squares inversion based on the iterative minimization of the sum of squared errors between log data and forward predictive model results were reported in the past. However, least-squares
5 solutions are uncertain due to their high sensitivity to noise. In addition to the wrong resistivity values in resistive beds, there also exist large oscillations in the inverted resistivity profile that is inconsistent with the true formation resistivity profile.

To enhance the stability of the least-squares inversion method against
10 noise, following the practice in image processing, Dyos first introduced an entropy term to the objective function via a Lagrange multiplier. Others introduced three algorithms based on the maximum flatness, maximum oil (resistivity) and minimum oil (resistivity). Without exception, all of these gradient-based methods require the calculation of the sensitivity matrix or
15 Jacobian matrix, namely, the apparent resistivity partial derivatives that represent the sensitivity of the apparent resistivity to various formation parameters such as bed boundaries and conductivity value in each bed. The calculation of the Jacobian matrix is time consuming for the following simple reason: for each iteration, if there are a total of N logging points, the number
20 of forward modeling calculation necessary is proportional to N, but the calculation of the Jacobian matrix is proportional to 0. Thus, with any realistic logging data set of a few hundred feet, the computational cost associated with updating the Jacobian matrix at each iteration becomes prohibitively expensive even on fast workstations. As a result, these algorithms are all
25 slow.

SUMMARY OF THE INVENTION

The present invention overcomes the foregoing and other problems with a method for determining a formation profile surrounding a wellbore wherein received field log data from a formation surrounding a wellbore is
30 used to establish a first formation profile using a neural network inversion

method. A synthetic log is generated from the first formation profile and the synthetic log is compared with a real log to determine whether the synthetic log converges with the real log. If they do not converge, the first formation profile is modified and a new synthetic log generated for a new comparison.

- 5 This process continues until the synthetic log converges with the real log at which point formation profile parameters based upon the synthetic log are output.

BRIEF DESCRIPTION OF THE DRAWINGS

10 A more complete understanding of the method and apparatus of the present invention may be obtained by reference to the following Detail Description when take in conjunction with the accompanying Drawings wherein:

FIGURE 1 illustrates an induction tool;

FIGURE 2 illustrates a well bore;

15 FIGURE 3a through 3b illustrate computer simulations of logs taken by a well sonde;

FIGURE 4 illustrates a method for determining formation parameters in a well bore;

20 FIGURE 5 illustrates a method of determining formation parameters in a well bore using a neural network inversion method;

FIGURE 6 is a flow diagram illustrating an embodiment of the present invention for determining parameters of an earth formation surrounding a well bore using a neural network inversion method;

25 FIGURE 7 is a flow diagram illustrating a first embodiment for determining parameters of an earth formation surrounding a well bore according to the present invention; and

FIGURE 8 is a flow diagram illustrating the determination of initial Jacobian matrix using a sliding window vector.

30

DETAILED DESCRIPTION OF THE EXEMPLARY EMBODIMENTS OF THE INVENTION

Generally, processing of log data from a well bore uses an iterative inversion scheme having essentially two parts. The first part contains a forward solver that generates a synthetic log from given test information. The second part contains criteria to modify the test formation. The criteria is based upon the differences between a synthetic log, corresponding to the test formulation, and the real log measured by the well tool. After the test formation has been modified, a new synthetic log is generated by the forward solver. This process is repeated iteratively until the difference between the synthetic log and real log is a less than a predefined tolerance. The output and the inversion algorithm are the parameters of the final test formation. It should be pointed out, however, that the repeated computation of the forward model in each iteration makes these methods computationally intensive and require a great deal of processing time.

This process is more fully illustrated with respect to FIGURE 4 wherein after receipt at step 500 of test formation data, a synthetic log is generated at step 505. A comparison is made at inquiry step 510 to determine differences between the generated synthetic log and the real log data as measured by the well tool. If inquiry step 510 determines that the difference between the synthetic log and the real log is not within a predetermined tolerance, the test formation is modified at step 515, and a new synthetic log is generated at step 505. This process repeats until the differences between the synthetic log and the real log are determined at inquiry step 510 to be within a predetermined tolerance at which point the test formation parameters associated with the synthetic log are output at step 520.

According to the present invention, the initial information for the iterative process is generated by a neural network (ANN) inversion method. This initial guess is closer to the final solution of the iterative method such that fewer iterations will be required to reach satisfactory convergence in the iterative method. This process is more fully illustrated in FIGURE 5. Upon receipt of

the test formation data at step 525, a synthetic log is generated at step 530 using a neural network inversion method. The differences between the generated synthetic log and the real log are again compared at inquiry step 535 to determine if they were within a predetermined tolerance. If not, the test formation is modified at step 540 and the process returns to step 530. This process repeats until the synthetic log and the real log are within predetermined tolerance at which point the test formation parameters are output at step 540.

In one alternative embodiment, an initial Jacobian matrix may be populated by a neural network (ANN) inversion method. The initial formation of the iterative process is generated by the neural network (ANN) inversion method. This initial guess is close to the final solution of the iterative method, so that fewer iterations, which may use the below described quasi Newton update, are needed to reach satisfactory conversions in the iterative method.

A formation resistivity profile generated from the neural network inversion is taken as the initial formation profile and fed as input into a gradient based inversion code. The Jacobian matrix, which represents the sensitivity of the log response to changes in formation profile is calculated based upon this initial profile. In subsequent iterations, a quasi Newton update (described below) such as the Boydens update method is used to approximate the Jacobian without any additional computational costs. This process continues until the difference between the field log and the calculated forward modeling results based on the inverted resistivity profile converges to a preset level.

Referring now to FIGURE 6, there is a flow diagram more fully illustrating the process. After receiving the field log data at step 150 an artificial neural network inversion process is performed at step 155 to determine an initial formation resistivity profile. A Jacobian matrix is calculated based upon the artificial neural network results at step 160. The Jacobian matrix represents the sensitivity of the log response to changes in the formation profile. A gradient based iterative inversion process performed

at step 165 and a log response is generated at step 170 based upon the new information. The log response is used to perform a comparison to determine differences from the existing field log at step 175. If the provided field log data converges within a predetermined level with the new response at inquiry step 5 180, the iteration is ended, and formation profile associated with the calculated log response is output at step 185. Otherwise, a quasi Newton update of the Jacobean matrix is performed at step 190 and control passes back to step 165.

Referring now to FIGURE 7, there is illustrated a flow diagram more 10 fully describing a gradient based iterative inversion process used in FIGURE 6. The field log data is received at step 30 and initially processed to determine at step 35 a conductivity or resistivity vector for the log data. A maximum flatness inversion algorithm constraint is applied to the formation parameters at step 40 in order to avoid the introduction of undesirable 15 artifacts. An initial Jacobian matrix is generated and populated at step 45 using a sliding window as will be more fully described with respect to FIGURE 8. A gradient based iterative inversion process is then performed at step 50 to generate a new log response at step 55 based upon the new information. The difference between the recalculated log response and the recorded field 20 log is determined at step 60 using a misfit vector. Inquiry step 65 determines if the provided field log data converges with the newly calculated response, and if so, the iterations are ended and a calculated log response is provided as the output formation profile at step 70. Otherwise, a quasi-Newton update of the Jacobian matrix is performed at step 75 utilizing the newly generated 25 log response and a new iterative inversion is performed at step 50. This process is more fully described below.

1. PROBLEM PARAMETRIZATION

30 Since an induction tool directly measures the formation conductivity, this parameter is used throughout the inversion process instead of resistivity.

At the end of the inversion process, it is converted to resistivity. Normally one has no *a priori* knowledge of bed boundaries. This lack of knowledge is compensated by discretizing the unknown formation into thin beds of equal thickness. This thickness can selectively take the values of 1/2 foot or 1 ft
 5 when the relative dip between borehole and formation is zero. Otherwise, the beds will have a thickness equal to $1 \text{ ft} / \cos(\theta)$ or $0.5 \text{ ft} / \cos(\theta)$ where θ is the relative dip angle. If there are a total of N such beds, the problem of inversion becomes one of finding a specific conductivity vector:

$$10 \quad \sigma = [\sigma_1, \sigma_1, \dots, \sigma_N]^T \quad (1)$$

such that the predicted log response based on this profile best matches the actual field log.

In order to keep all conductivity values positive, a traditional
 15 transformation is introduced by replacing the conductivity values with their logarithmic values during the inversion process:

$$q = [q_1, q_2, \dots, q_N]^T, \text{ where } q_n = \log \left(\frac{\sigma_n}{\sigma_0} \right) \quad n = 1, 2, \dots, N \quad (2)$$

20 and $\sigma^0 = [\sigma_1^0, \sigma_2^0, \dots, \sigma_N^0]^T$ is some initial conductivity profile which is typically chosen to be a uniform profile. Similarly, if there are a total of M logging data points in the field log, this field data is combined into a column vector of the form:

$$25 \quad \sigma_A = [\sigma_a(z_1), \sigma_a(z_2), \dots, \sigma_a(z_M)]^T \quad (3)$$

And the inverted conductivity profile is written as:

$$\sigma_{inv} = [\sigma_{inv}(z_1), \sigma_{inv}(z_2), \dots, \sigma_{inv}(z_M)]^T = [\sigma_{inv1}, \sigma_{inv2}, \dots, \sigma_{invN}]^T \quad (4)$$

The measured apparent conductivity of a multi-coil induction tool at a given logging depth z in a formation with conductivity profile σ can be written
5 as:

$$\sigma_a(z, \sigma) = \frac{1}{K} \sum_{t=1}^T \sum_{r=1}^R V_{rt}(z, \sigma) = \frac{1}{K} \sum_{t=1}^T \sum_{r=1}^R V_{rt}(z, q) = \sigma_a(z, q) \quad (5)$$

where

10

$V_{rt}(z, q)$ = voltage generated on the r -th receiver due to the t -th transmitter.

z = logging depth;

T = total number of transmitters in the subarray;

15

R = total number of receivers in the subarray;

K = tool constant for the subarray.

20

Since Eq. 5 holds at every logging position $z = z_m$ ($m = 1, 2, \dots, M$), one can construct an apparent conductivity vector over the whole logging interval as:

$$\sigma_a(q) = [\sigma_a(z_1, q), \sigma_a(z_2, q), \dots, \sigma_a(z_M, q)]^T \quad (6)$$

Because $\sigma_a(q)$ is a nonlinear function of the formation conductivity vector σ and hence q , just as in any nonlinear problem, one needs to first linearize the
25 response function. To this end, $\sigma_a(q)$ is expanded into a Taylor series about a conductivity profile q as:

$$\sigma_a(q + x) = \sigma_a(q) + A(q)x + O(x^2) \quad (7)$$

where x is a perturbation vector representing a small change in the transformed conductivity vector. A is the $M \times N$ sensitivity or Jacobian matrix whose elements are given by:

$$A_{mn} = \frac{\partial \sigma_a(z_m, q)}{\partial q_n}, \quad m = 1, 2, \dots, M; \quad n = 1, 2, \dots, N \quad (8)$$

When the Euclidean norm of $\|x\| = \sqrt{x^T x}$ is small, the higher order terms can be neglected. Eq.7 then represents an approximate linear dependence of the measured apparent conductivity on the transformed conductivity vector q .
 10 Since analytical expressions for the derivatives in Eq.8 are not available, forward-difference approximations are used based on the following finite-difference expression:

$$A_{mn} = \frac{\sigma_a(z_m, q') - \sigma_a(z_m, q)}{\delta}, \quad m = 1, 2, \dots, M; \quad n = 1, 2, \dots, N \quad (9)$$

15

$$q = [q_1, q_2, \dots, q_j, \dots, q_N]^T,$$

$$q' = [q_1, q_2, \dots, q_j + \delta, \dots, q_N]^T$$

where δ is a predetermined small increment in the transformed conductivity.

20

2. THE MAXIMUM FLATNESS INVERSION ALGORITHM

The linearized Eq.7 can be rewritten as:

$$Ax = b \quad (10)$$

where the direct error vector or direct misfit vector is defined as:

$$b = \sigma_A - \sigma_a(q) \quad (11)$$

Since there are typically more logging data points than the number of unknown conductivity values, Eq.10 is a standard over-determined least-squares (LS) problem, which can be solved readily to give:

5

$$x=[A^T A]^{-1}A^T b . \quad (12)$$

To reduce overshoot in the least-squares solution, usually a damping term is introduced into Eq.10 to form the damped least-squares (DLS) problem:

10

$$\begin{bmatrix} A \\ \lambda \end{bmatrix} x = \begin{bmatrix} b \\ 0 \end{bmatrix} \quad (13)$$

where λ is a damping factor. The solution of (13) can be written as:

15

$$x = [A^T A + \lambda^2 I]^{-1} A^T b \quad (14)$$

This solution of the perturbation vector x is added to the initial conductivity profile q to yield the transformed conductivity profile of $q + x$. The resultant conductivity profile is then obtained via transformation (Eq.2) as:

20

$$\sigma_{q_n+x_n} = \sigma_{q_n} e^{x_n}, \quad n=1,2,\dots, N \quad (15)$$

Using k as iteration index such that q^k denotes the transformed conductivity profile vector and x^k the perturbation vector at the k -th iteration, one can rewrite Eq.15 into the following iterative formula:

25

$$q^{k+1} = q^k + x^k \quad (16)$$

In order to stabilize the least-squares solution, some sort of regularization process needs to be introduced to the aforementioned

procedure. Among the various kinds of regularization methods, the method of maximum entropy has enjoyed wide success in various branches of science, from the sharpening of radio astronomy data to pattern recognition, to x-ray crystallography. The maximum entropy principle was originally proposed as a
 5 general inference procedure by Jaynes based on Shannon and Weaver's pioneering work on information theory.

For discrete conductivity profile such as the case of earth formations, the entropy functional is written as:

$$10 \quad S\{\sigma\} = - \sum_{n=1}^N \frac{\sigma_n}{C} \left[\ln \left(\frac{\sigma_n}{\sigma_n^0} \right) - 1 \right], \quad C = \sum \quad (17)$$

The negative sign means that this entropy is the so-called negentropy since it is the negative measure of the configurational information in the conductivity profile. The necessary condition for entropy to be the maximum is:

$$15 \quad \frac{\partial S}{\partial \sigma} = 0. \quad (18)$$

It is straightforward to show that this leads to:

$$20 \quad \sigma(z) = \sigma_0 \quad (19)$$

Namely, the entropy functional reaches its maximum when there is absolutely no feature in the conductivity profile. i.e., a homogeneous profile will have the highest entropy while the introduction of any feature into the profile inevitably
 25 reduces the entropy. Thus, by constraining the least-squares problem with the requirement that entropy be the maximum, one ensures that the inverted conductivity profile thus obtained will be the flattest or smoothest possible profile that is consistent with the original field data.

With the transformation in Eq.2, the maximum entropy condition (Eq.19) is expressed in terms of the transformed conductivity vector q as:

$$q = 0 \quad (20)$$

5

Since $q^{k+1} = q^k + x^k$ from Eq.16, setting $q^{k+1} = 0$ results in the following maximum entropy constraint:

$$x = -q \quad (21)$$

10

The utilization of a Lagrange multiplier α enables one to combine the damped least-squares problem Eq.10 and the maximum entropy constraint (Eq.21) together to form a joint equation:

$$\begin{bmatrix} A \\ \alpha I \\ \lambda \end{bmatrix} x = \begin{bmatrix} b \\ -\alpha q \\ 0 \end{bmatrix} \quad (22)$$

15

where I is an $N \times N$ identity matrix. From Eq.24, the entropy constrained conductivity profile solution is obtained:

$$x = [A^T A + \alpha^2 I + \lambda^2 I]^{-1} [A^T b - \alpha^2 q] \quad (23)$$

20

In essence, the starting point of the maximum flatness algorithm is the assignment of $q_n = 0$ ($n = 1, 2, \dots, N$). Namely, a homogeneous conductivity profile (see Eq.2) is assumed. This homogeneous conductivity profile has a maximum entropy or maximum flatness according to Eq.19. In subsequent iterations, the profile is modified so as to minimize the misfit $\|b\| = \|\sigma_A - \sigma_a^k\|$ between the field data σ_A and the predicted data σ_a^k .

25

3. INVERSION IN TERMS OF RELATIVE MISFIT VECTOR

The misfit vector defined in Eq.11 is directionally proportional to conductivity and leads to inversion results that are biased toward highly
 5 conductive zones. Alternatively, one can introduce a relative error vector or relative misfit vector b_r with the subscript "r" to distinguish it from the direct error vector b defined in Eq.11. Elements of the relative error vector are those of the direct error vector normalized by apparent conductivity:

$$10 \quad b_{rm} = \frac{\sigma_A(z_m) - \sigma_a(z_m, q)}{\sigma_A(z_m)} = \frac{b_m}{\sigma_A(z_m)}, \quad m = 1, 2, \dots, M \quad (24)$$

It is straightforward to show that elements of the new Jacobian matrix for this relative misfit vector are given by:

$$15 \quad A_{rnm} = \frac{1}{\sigma_a(z_m, q)} \frac{\partial \sigma_a(z_m, q)}{\partial q_n}, \quad m = 1, 2, \dots, M; \quad n = 1, 2, \dots, N \quad (25)$$

The effect of the relative misfit vector b_r on the inversion is opposite to that of the previously defined direct misfit vector b in that the former is biased toward regions of higher resistivity while the latter is biased toward more
 20 conductive regions. Which algorithm should be used for a given field log should depend on the quality of the field log. If the field log data is "clean" in the sense that noise is known to be low, then the relative error algorithm usually yields better results. On the other hand, since log data in highly resistive beds are more susceptible to noise, for noisy data, the direct error
 25 algorithm is more robust against noise.

4. QUASI-NEWTON UPDATE OF THE SENSITIVITY MATRIX

Because of the requirement of the sensitivity or Jacobian matrix, all algorithms discussed so far suffer the same problem of high computational cost. Specifically, given a total of M logging points, a total number of N discretized beds in the formation, and the total of $k_{\max}$ iterations, the total number of necessary calls to the forward routine is given by

$$n_f = (MxN + M)k_{\max} = M(N + 1)k_{\max} \approx M \cdot N \cdot k_{\max} \quad (26)$$

Since the most time-consuming portion of the iteration is the calculation of the Jacobian, if one can reduce this part of the inversion, the whole algorithm can be accelerated significantly. A quasi-Newton updating technique is applied to the Jacobian matrix to reduce the inversion time. To this end, consider first a one-dimensional function $f(q)$, its derivative can be approximated by the well-known secant method:

$$f'(q^{k+1}) \approx \frac{f(q^{k+1}) - f(q^k)}{q^{k+1} - q^k}, \text{ or } f'(q^{k+1})(q^{k+1}) \approx f(q^{k+1}) - f(q^k) \quad (27)$$

Generalization of this formula to the N-dimensional logging problem leads to:

$$A^{k+1}x = y^k \quad (28)$$

where

$$x^k = q^{k+1} - q^k \quad (29)$$

$$y^k = \sigma_a^{k+1}(q^{k+1}) - \sigma_a^k(q^k)$$

Instead of using the Jacobian matrix A, a matrix update $B^{k+1} = B^k + U^k$ is used that satisfies the quasi-Newton condition:

$$B^{k+1}x^k = y^k \quad (30)$$

Notice that the quasi-Newton condition only provides N equations for the $M \times N$ matrix B^{k+1} so it cannot uniquely determine the update matrix U^k . It can easily be shown that the quasi-Newton condition can be satisfied by adding a rank-one matrix update to B^k . This can be accomplished by introducing

5

$$B^{k+1} = B^k + uv^T \quad (31)$$

for some N -vectors u, v . Applying the quasi-Newton condition to Eq.31 leads to:

10

$$B^{k+1}x^k = (B^k + uv^T)x^k = y^k, \text{ or } u = \frac{1}{v^T x^k} (y^k - B^k x^k) v^T \quad (32)$$

assuming $v^T x^k \neq 0$. Since one already has x^k and clearly $\begin{bmatrix} x^k \\ x^k \end{bmatrix}^T x^k \neq 0$, the logical choice of $v = x^k$ leads to Broyden's update formula:

15

$$B^{k+1} = B^k + \begin{bmatrix} y^k - B^k x^k \\ \begin{bmatrix} x^k \\ x^k \end{bmatrix}^T \begin{bmatrix} x^k \\ x^k \end{bmatrix} \end{bmatrix} \quad (33)$$

which obviously satisfies the quasi-Newton condition Eq.30.

The advantage of the quasi-Newton update algorithm over the direct
20 Jacobian algorithm is obvious. In the quasi-Newton update algorithm, the Jacobian matrix is calculated only once at the very beginning of inversion process. In subsequent iterations, the Jacobian is updated with little computational expense since the data needed for this update is already available after the forward modeling that is needed to calculate the misfit
25 vector. Thus, the total number of calls to the forward modeling routine is:

$$n_{Q.N.} \approx M \cdot k_{\max} \quad (34)$$

Compared with Eq.26, the algorithm with quasi-Newton updates reduces the number of calls to the forward routine by a factor that is equal to the total number of logging data points. It is this saving in CPU time that makes the fast inversion possible.

- 5 It should be pointed out that the so-called rank-one quasi-Newton update is mentioned in the above. It is obviously possible to use other types of quasi-Newton update methods such as the symmetric rank-one update, or the family of rank-two updates, such as the Davidon-Fletcher-Powell (DFP) update, Bryoden-Fletcher-Goldfarb-Shanno (BFGS) update.

10

5. SPEED UP OF THE CALCULATION FOR THE INITIAL JACOBIAN MATRIX

- Referring now to FIGURE 8, although the quasi-Newton update speeds up the inversion in subsequent iterations by avoiding direct calculation of the Jacobian matrix, before the start of the iteration procedure, the Jacobian matrix still needs to be initially populated. Fortunately, with the application of the maximum flatness algorithm to the provided log data, the initial conductivity profile is a homogeneous one. This enables one to greatly reduce the number of calculations needed. Specifically, Except at the two beds at the two end points of the formation of interest where only a 2-bed formation is needed, the response of the induction tool to a simple 3-bed formation is needed to populate the whole Jacobian matrix. The 3-bed formation consists of a center bed having a thickness equal to the parameterized bed thickness (discussed in section 2) and two semi-infinite shoulder beds. With the conductivity of each bed set at step 90 to the average of the logging data apparent conductivity, the response of the induction tool is calculated at step 95. This necessitates only a single call to the forward routine. Then the conductivity of the center bed is incrementally changed at step 100 and the response of the tool is calculated at step 105. Forward difference (Eq.7) is then used to calculate the derivatives at step 110,

which forms a single column vector of the Jacobian matrix. By sliding the 3-bed formation and this single column vector across the whole formation of interest at and keeping track of all the indices meticulously, the whole Jacobian matrix is populated at step 115. Compared to the brute force
5 forward difference method, this technique reduces the CPU time required for the initial Jacobian matrix by a factor of $M / 3$ where M is the total number of logging data points.

The previous description is of a preferred embodiment for implementing the invention, and the scope of the invention should not necessarily be limited
10 by this description. The scope of the present invention is instead defined by the following claims.

WE CLAIM:

1. A method for determining a formation profile surrounding a well bore, comprising the steps of:

(a) receiving field log data for a formation surrounding the well bore;

5 (b) performing a neural network inversion method to generate an initial formation resistivity profile; and

(c) determining an initial vector from the field log data, said initial vector being at least one of a conductivity or resistivity vector;

10 (d) generating a Jacobian matrix using a sliding window and the initial vector being at least one of a conductivity or resistivity vector;

(e) generating a synthetic log from the initial formation profile;

(f) determining if the synthetic log converges with a real log;

(g) modifying the initial formation profile and repeating steps (e) and (f) if the synthetic log does not converge with the real log;

15 (h) outputting formation profile parameters based upon the synthetic log if the synthetic log converges with the real log.

2. The method of Claim 1, wherein the step of modifying further comprises the step of:

20 performing a quasi-Newton update of the initial formation profile and repeating step (e) and (f) in the synthetic log does not converge with the real log.

3. The method of Claim 1, wherein the step of generating further comprises the step of calculating a log response responsive to the Jacobian matrix.

25

4. The method of Claim 1, wherein the step of generating the Jacobian matrix using the sliding window further comprises the steps of:

determining a single column vector of the Jacobian matrix; and

30 sliding the single column vector and a three bed formation across the formation to populate the Jacobian matrix.

5. The method of Claim 1, further including the step of applying a maximum flatness inversion algorithm to the received field log data.

6. The method of Claim 1, wherein the step of determining further
5 compromises the step of comparing the determined log response to the received field log data to determine any differences therebetween.

7. The method of Claim 2, wherein the step of performing further
10 compromises the step of performing a quasi-Newton update responsive to the determined log response and a presently existing Jacobian matrix.

8. The method of Claim 3, wherein the step of calculating further compromises performing a gradient based iterative invention.

15 9. A method for determining a formation profile surrounding a well bore, comprising the steps of:

(a) receiving field log data for a formation surrounding the well bore;

(b) performing a neural network inversion method to generate an initial formation resistivity profile; and

20 (c) determining an initial vector from the field log data, said initial vector being at least one of a conductivity or resistivity vector;

(d) generating a Jacobian matrix using a sliding window and the initial vector;

(e) calculating a log response responsive to the Jacobian matrix;

25 (f) determining if the log response converges with the received field log data;

(g) performing a quasi-Newton update of the Jacobian matrix and repeating step (e) and (f) if the log response does not converge with the received field log data; and

30 (h) outputting the formation profile based upon the log response if the log response converges with the received field log data.

10. The method of Claim 9, further included the step of applying a maximum flatness inversion algorithm to the received field log data.

11. The method of Claim 9, wherein the step of determining further comprises the step of comparing the determined log response to the received field log data to determine any differences therebetween.

12. The method of Claim 9, wherein the step of performing further comprises the step of performing a quasi-Newton update responsive to the determined log response and a presently existing Jacobian matrix.

13. The method of Claim 9, wherein the step of calculating further comprises performing a gradient based iterative inversion.

14. A method for determining a formation profile surrounding a well bore comprising:

performing a neural network inversion method to generate an initial formation resistivity profile; and

determining an initial vector from the field log data, said initial vector being at least one of a conductivity or resistivity vector;

generating a Jacobian matrix using a sliding window and the initial vector;

substantially determining if the initial formation profile represents a real formation profile;

modifying the initial formation profile until it substantially represents the real formation profile;

outputting formation profile parameters based upon the initial formation profile when the initial formation profile substantially represents the real formation profile.

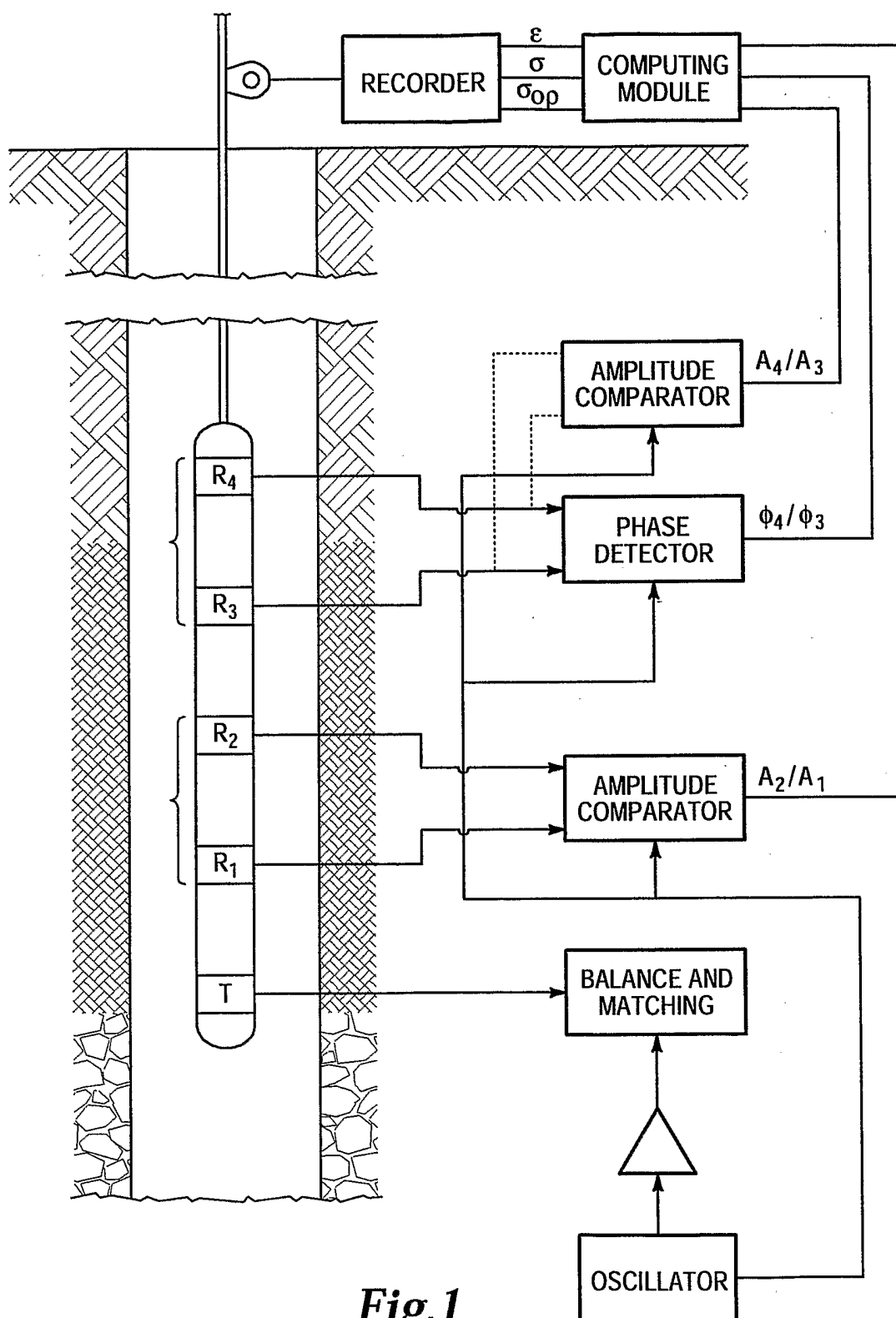
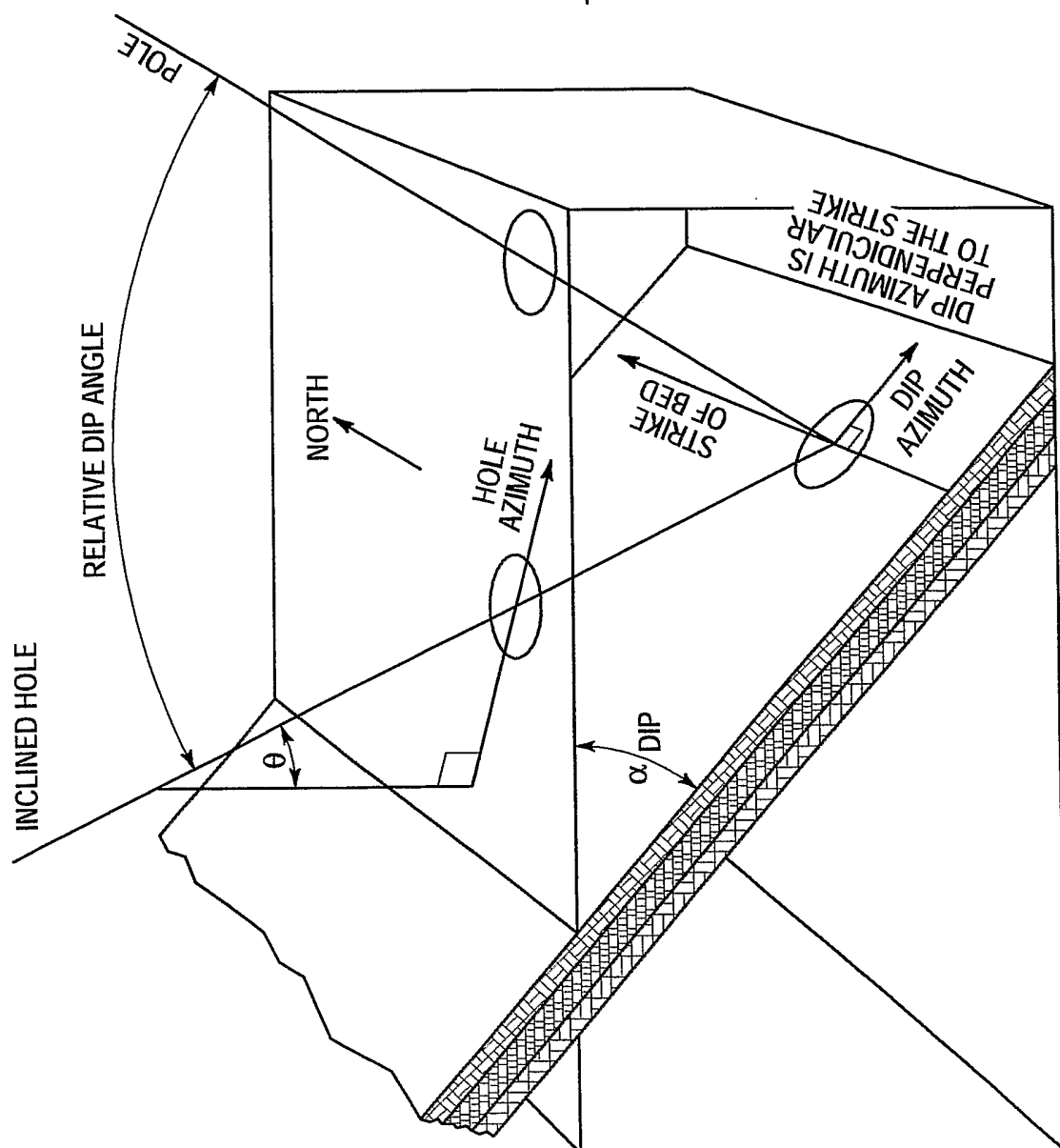
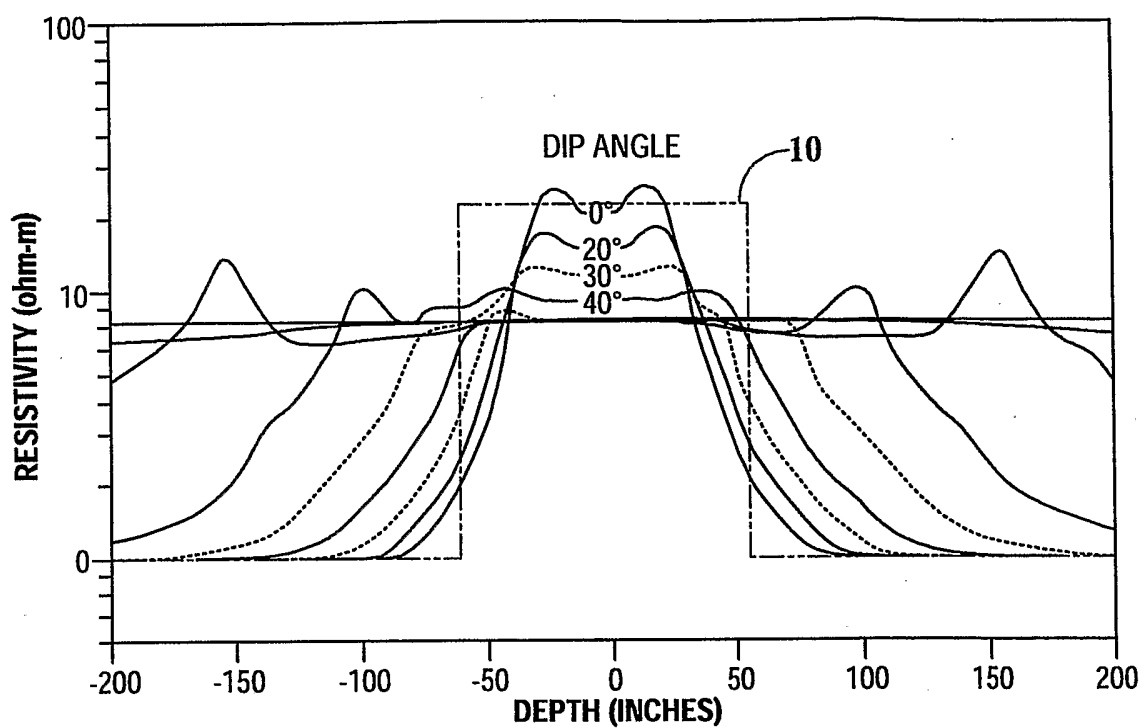
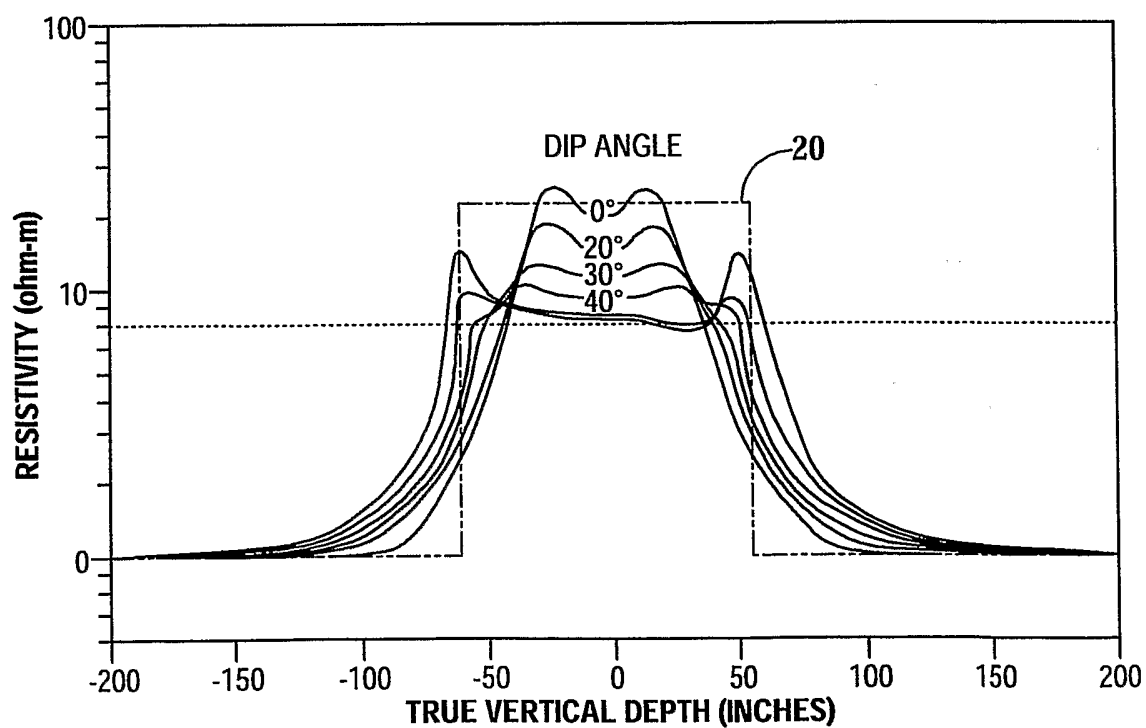
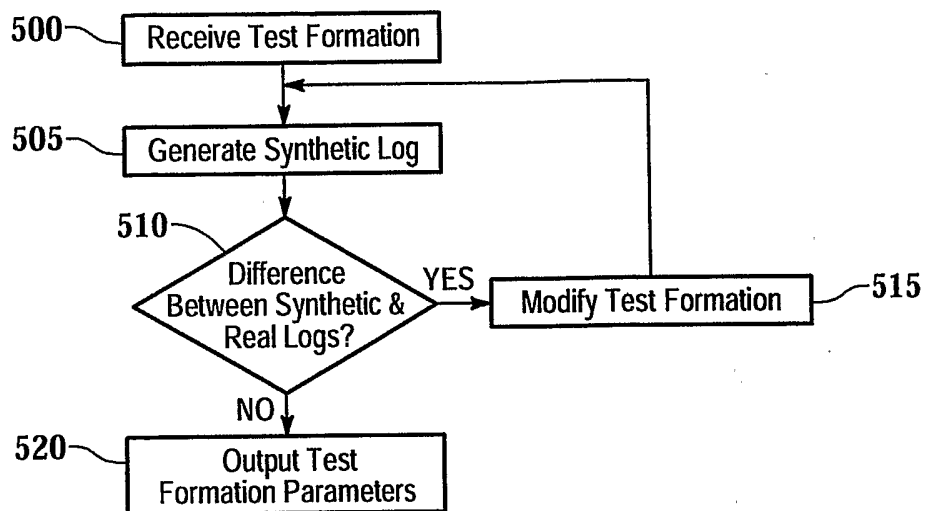
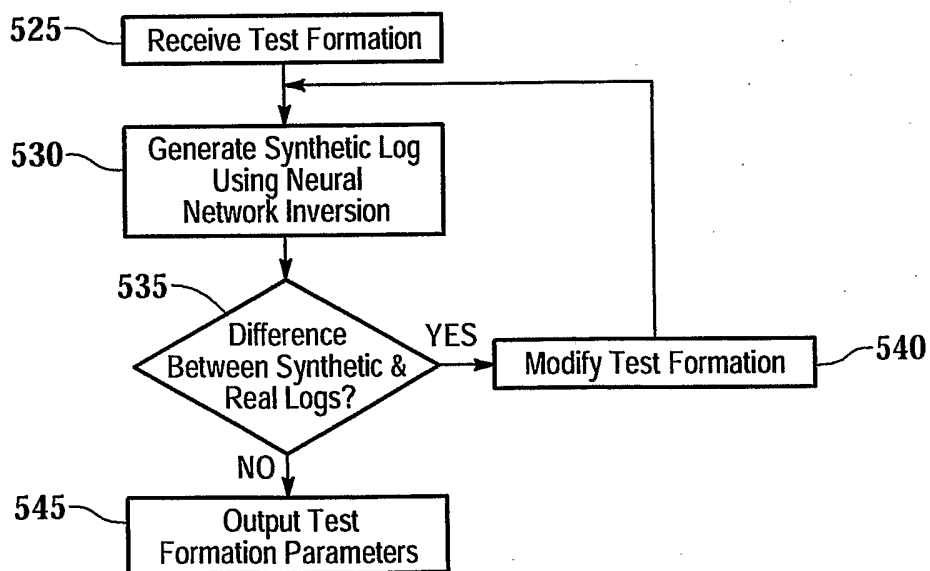


Fig.1
(PRIOR ART)

Fig. 2



*Fig.3A**Fig.3B*

*Fig.4**Fig.5*

