DETERMINATION OF REGIONAL DIP AND FORMATION PROPERTIES FROM LOG DATA IN A HIGH ANGLE WELL

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ABSTRACT

A computationally efficient method for determining regional dip angles and formation properties in high angle wells is presented. As a first step, single or multiple logs are processed to obtain similar features. The feature extraction process is speeded up by observing that variation in the formation properties of a high angle well is typically far less than that of a vertical well. Consequently, log data can be appropriately filtered and considerably down-sampled while preserving the essential features of the log. A wavelet-based method is used for multilevel decomposition of log data. Once locations of similar features are determined, tool trajectory and other information may be combined to select a few features that satisfy certain operating and geological constraints, namely, beds cannot cross each other, dips should be consistent with other measurements, etc. These features, in conjunction with the logs and tool trajectory, provide an initial set of dip angles and formation parameters. Estimates of dip angles and formation parameters are improved by an iterative procedure that minimizes the error between computed and measured logs.

INTRODUCTION

A typical high angle well is shown in Figure 1. Information about dip angles for such cases becomes very important for many reasons, including well placement and formation evaluation. Existing techniques provide dip angles that are valid at small scales (those obtained by FMI, LWD density images, Dip Meters, for instance) or large scales (from seismic data). Here small scales may be a few 10's of centimeters whereas large scales are tens of meters. Quite often, particularly for well placement applications, it is useful to know dip angles and formation properties at intermediate scales so that the well can be steered in the appropriate formation layer.

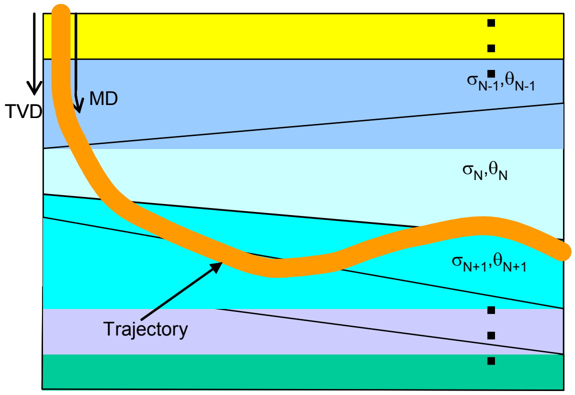


Figure 1: A typical high angle well formation (σ: conductivity, θ: dip angle).

In this paper, we present a novel method for computing regional dip angles and formation properties at intermediate scales from high angle / horizontal well data. The steps to estimate dip angle and formation properties are summarized in Figure 2. First, single or multiple logs, from single or multiple tools are processed to obtain similar features, represented by vectors $\{x_i, y_i\}$. Such features may, for example, include those portions of the logs that are mirror images of each other, indicating that the tool has re-entered the same layer (see Figure 3). Once locations of similar features are determined, tool trajectory and other information may be combined to select a few, $\{u_i^0, v_i^0\}$, that satisfy certain operating and geological constraints, namely, beds cannot cross each other, dips should be consistent with other measurements, etc. The vectors $\{u_i^0, v_i^0\}$ correspond to bed locations.

Computed dip angles and formation properties give an initial formation model. A forward model is used to generate logs. Estimates of dip angles and formation parameters can be improved iteratively by minimizing error between computed and measured logs.

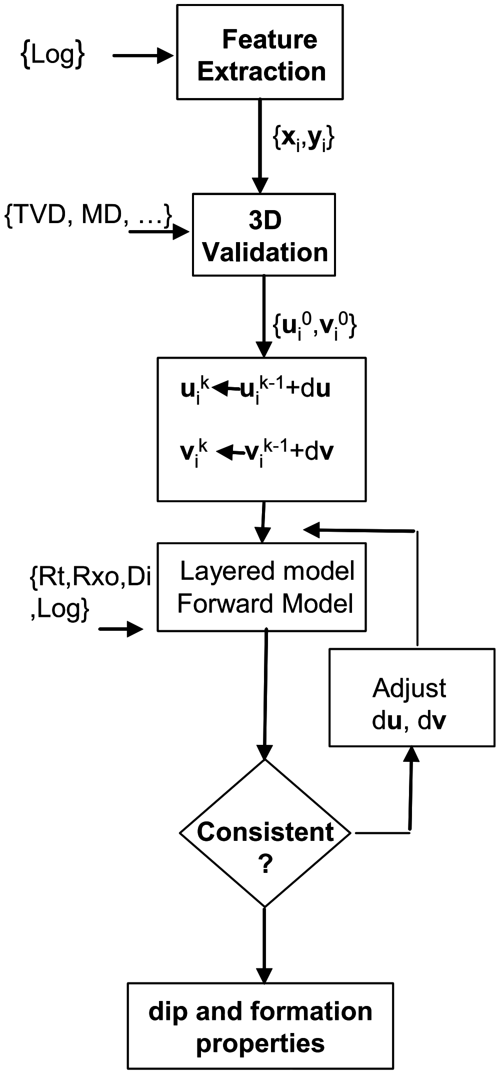


Figure 2. Steps for computing regional dip angles and formation properties.

FEATURE EXTRACTION

Consider a log shown in Figure 3. By looking at the log, we can see that sections A and A' are mirror images of each other. The gradient around these sections are high. These sections may, therefore, lie near a bed boundary. As a first step, the features are extracted from the log. There are several feature extraction methods [1], two such methods are described below. These methods can be used individually or in combination.

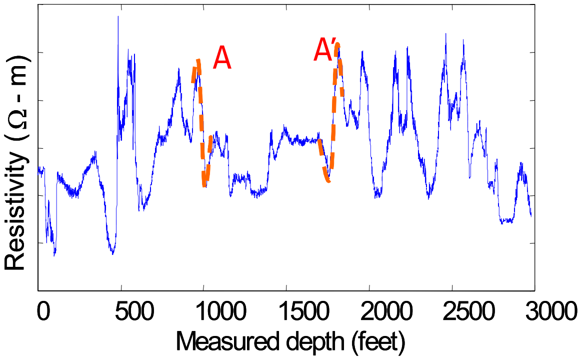


Figure 3. Resistivity log from a high angle well. Sections A and A' are mirror images of each other indicating that the tool may have re-entered the same layer.

Method 1: Given a log $f(x)$, define $d(\tau,x) := f(x) - f(\tau - x)$. Observe that $d(\tau,x)$ is the difference between the original log $f(x)$ and its reversed version shifted by τ. So, if there are regions in $f(x)$ that are mirror images, then for some set of τ, there will be regions in $d(\tau,x)$ that will be zero or less than a certain pre-selected threshold. By varying τ, we can account for all possible similar features.

For efficient and robust feature extraction, it is important to work with filtered logs that are smoother than the original logs. We have used the wavelet decomposition method [2]. In this method, not only do we get a smoother log, but the number of data points is also reduced. In wavelet decomposition [3], a given signal, f, is passed through a series of lowpass filter, ϕ, called a scaling filter, and a high pass filter, ψ, called a wavelet filter. After filtering, the signal is downsampled by a factor 2. The lowpass filtered signal is further divided into lowpass and highpass filter components, and the sequence is repeated. These steps are shown in Figure 4.

Figure 5 shows various components of a log using Daubechies' wavelet with filter length as four. As mentioned before, for each level of decomposition, the number of data points is roughly halved. For example, the original log, shown in the top of Figure 5, has 2991 data points. The lengths of a_1, a_2, a_3, and a_4 are 1497, 750, 377, 190, respectively. The highpass components, w_1, w_2, w_3, and w_4 represent differences at respective levels and have the same lengths as a_1, a_2, a_3, and a_4, respectively. The signal a_4, although much smaller in size, preserves the essential elements of the original signal. We have used this signal for feature extraction. The results are shown in Figure 6. Only the first five similar features are shown.

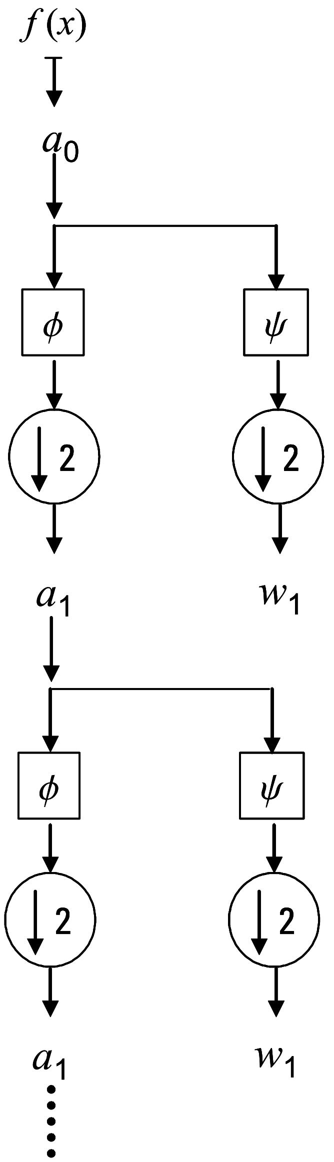


Figure 4: Multi-level decomposition of a signal using wavelets.

Method 2: In this method, we can use multiple logs from the same tool or different tools. Phase and attenuation resistivities measured by an LWD resistivity tool are plotted in Figure 7. Layering of earth formation affects phase and attenuation resistivities differently. Regions where the curves start separating indicate boundaries. These separations can then be used to identify similar features and thus bed boundaries. It is clear that the separation regions indicated by Figure 7 match with those in Figure 6 (features 1-1, 3-3, and 5-5, for example).

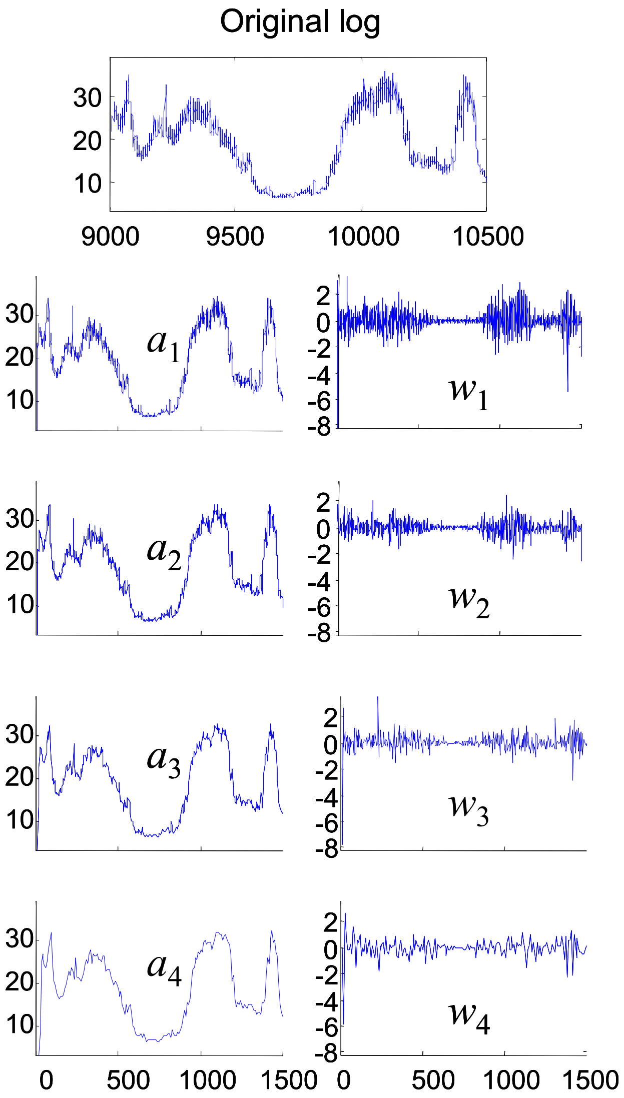


Figure 5: Wavelet decomposition of a log. The horizontal axes in plots for $a_1 \dots a_4$, and $w_1 \dots w_4$ are measured depth starting at 9000 feet.

Similar features may also be extracted by first squaring the log (i.e., representing the given log as piecewise constant), and then using the regions with large amplitude variations as templates and cross-correlating with the reversed signal (or keep the signal as it is and reverse the template) to identify similar features.

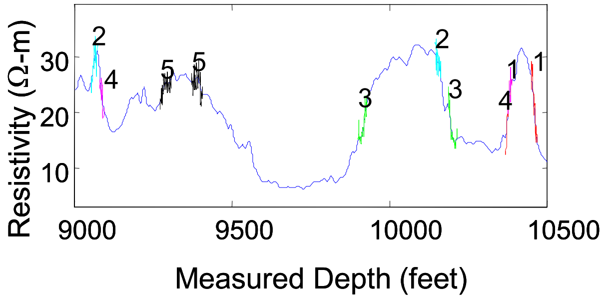


Figure 6. Data a_4 is used to extract features by Method 1.

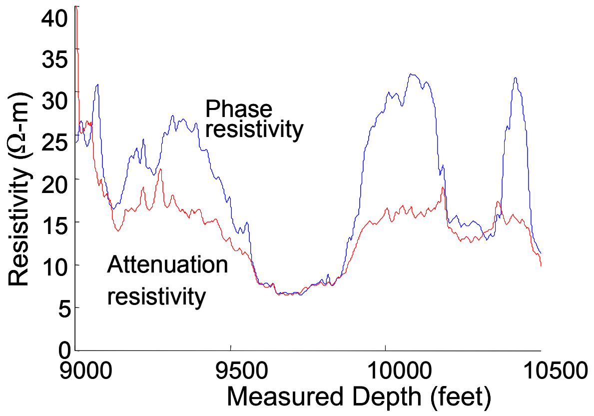
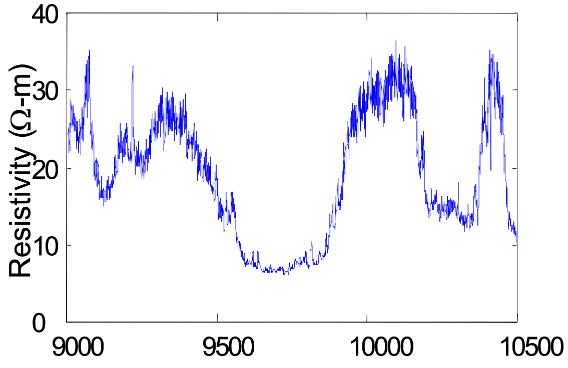


Figure 7. Feature extraction using Method 2.

COMPUTATION OF DIP AND FORMATION PROPERTIES

We have used Method 1, for further analysis and have combined with the tool trajectory to select 1-1 and 3-3 (see Figure 6) as acceptable features. Others, 2-2, 4-4, 5-5, either give inconsistent inclination, or result in the crossing of formation layers which is nonphysical. Based on 1-1 and 3-3, a layered model is generated as shown in Figure 8. Formation resistivities are assigned to each layer. The values are determined by taking median of resistivity from the original log for each region. The highest and lowest levels can be determined from the logs and the tool trajectory.

Using the layered model and tool trajectory shown in Figure 8, an electromagnetics forwarding modeling generates a synthetic (reconstructed) log. The results are shown in Figure 9. It is worth mentioning here results in Figure 8 and 9 are generated automatically by the algorithm and it is very fast (less than a second per point). An optimization algorithm is used to improve the accuracy. Figure 10 shows results from such an optimization. Further improvement can be achieved by increasing the number of layers. As can be seen from these results, Figure 8 gives fairly good estimates of dip angle and formation properties.



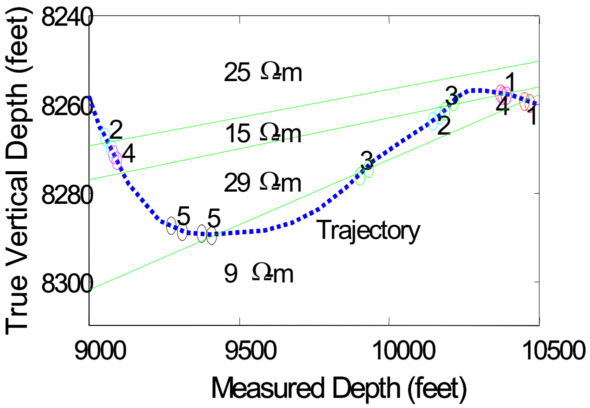


Figure 8. A layered formation model obtained by combining similar features with tool trajectory.

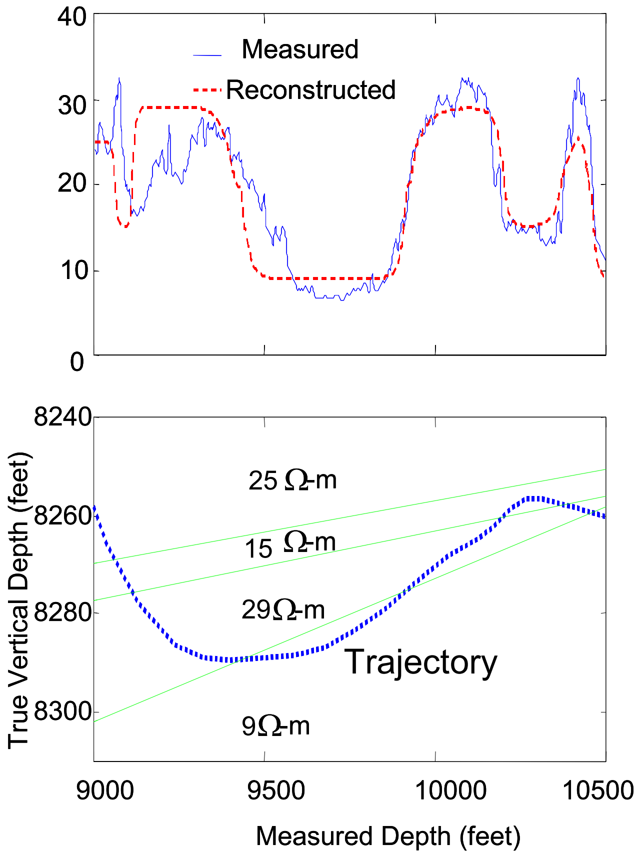


Figure 9. Measured and reconstructed logs.

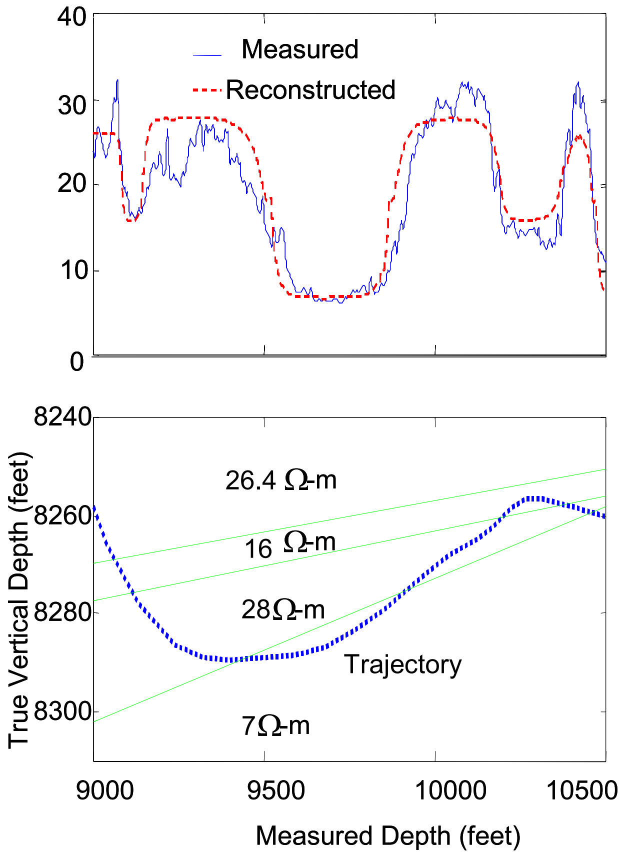


Figure 10. Measured and reconstructed logs after optimization.

CONCLUSIONS

The method presented here computes an optimum set of formation dips and bed properties based on log data from a high angle / horizontal well which crosses bed boundaries more than once. Key elements of this work are simplification via filtering of redundant data, extraction of relevant features, and automatic generation of an approximate model. In many cases, the approximate model may be good enough. The estimates can be improved by an optimization technique. The result is a potentially significant reduction in analyst work load and computation time for log simulation, thus improving the ability to provide timely results in support of both well placement and formation evaluation applications. The formation dip data provided by this technique is at a scale intermediate between seismic and the wellbore.

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Jaideva C. Goswami received his Ph.D. in Electrical Engineering in 1995 from Texas A&M University. After spending one year at the University of Illinois at Urbana-Champaign as a Visiting Research Fellow, he joined Schlumberger in 1996 where he is currently a Principal Engineer. He was a Professor in the Department of Electronics and Communication Engineering at the Indian Institute of Technology, Kharagpur during 2005-6. Besides publishing over forty papers in Journals and Conference proceedings, he has contributed three book chapters and is a coauthor of the book "Fundamentals of Wavelets: Theory, Algorithms and Applications," John Wiley & Sons, New York, 1999. He holds nine U.S. Patents. He is an Associate Editor of Journal of Radio Science. At Schlumberger he has been involved with the design of several well-logging tools and the development of various interpretation algorithms. His research interests include computational electromagnetics, signal processing, optimization, nuclear magnetic resonance, wireless telemetry, and subsurface sensor design and data analysis. He is a member of SPWLA, AGU, and a Senior Member of IEEE.

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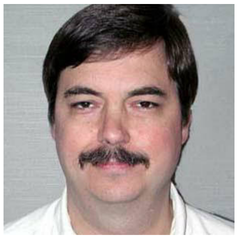

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