Stratigraphic Interpretation of Wireline log by Application of Spectral Trend Analysis

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Keywords

Maximum Entropy Spectral Analysis, INPEFA, Sequence Stratigraphy,

Abstract

Spectral trend attribute analysis is a method for interpreting wireline log data. This method uses a prediction error filter to calculate a new data series. It involves applying a prediction error filter to the data, which creates a new series that represents the numerical difference between the predicted and actual values at each depth. This series, known as the Prediction Error Filter Analysis (PEFA) curve, provides geological insights into the continuity or discontinuity of the stratigraphic succession. Larger errors in the PEFA curve indicate significant breaks in the succession. By numerically integrating the PEFA curve, we obtain the Integrated PEFA (INPEFA) curve, which reveals hidden trends and patterns that may not be readily visible in the original log data. The INPEFA curve is particularly useful for subdividing geological successions and identifying key surfaces. It enhances the understanding of the stratigraphic analysis of well logs. In this paper an overview of the fundamental principles behind spectral trend attribute analysis has been presented. This method offers a valuable tool for geologists seeking innovative approaches to analyze and interpret well logs.

Introduction

Quantitative interpretation of Wireline log data have traditionally been used in petrophysics and seismic data calibration. But the application of wireline log data in geological interpretation has been more qualitative in nature (Rider, 1996). However, there exists a significant potential for a more quantitative approach to the geological analysis of log data. In this paper, an application quantitative interpretation has been presented that directly contributes to the stratigraphic interpretation of well logs. This approach expands the possibilities for a more rigorous and data-driven understanding of the geological aspects of log data interpretation.

Most well logs consist of regularly spaced measurements of physical quantities, such as Gamma Ray, Resistivity etc. Since a log represents a series of values at regular intervals, it lends itself to various time-series analysis techniques, including the focus of this paper: spectral (frequency) methods. These methods leverage the inherent structure of the log data to analyze and interpret the underlying geological information.

According to the principle of superposition, it is generally understood (although not universally applicable) that deeper sections of a borehole correspond to older geological strata. However, the relationship between depth and geological age is not consistently linear for two main reasons: (1) rate of deposition can vary significantly, and (2) the depositional process is often discontinuous at a given location (Sadler, 1999). Consequently, a series of data points sampled at regular intervals along a borehole appears regular only in terms of depth. From a geological time perspective, the data points are far from regular. The more crucial question is whether this irregularity invalidates the application of classical "time-series" methods in the geological interpretation of wireline log data? Fortunately it does not.

Motivation

The utilization of spectral methods originated from the interest in detecting Milankovitch rhythms within stratigraphic data. It is hypothesized that climate changes driven by orbital forcing can leave an imprint in the geological layers due to the influence of varying insolation on erosion, transport, and deposition processes. The verification of this hypothesis in recent decades (Schwarzacher, 1993; Weedon, 2003) has opened up opportunities for identifying individual climate cycles and utilizing them for high-resolution correlation purposes. Since the predicted Milankovitch periods span tens to hundreds of thousands of years, there exists the potential avenue for substantial improvements in resolution compared to conventional methods such as biostratigraphy and seismic stratigraphy. Recognizing the possibility of detecting Milankovitch cycles within wireline logs, a method have been developed by for the spectral analysis ((Nio et al., 2005)) of these logs.

One challenge in applying spectral methods like Fourier analysis to geological time-series data is the presence of significant but unknown discontinuities and changes in data properties, as mentioned earlier. Wireline logs exhibit variations in spectral properties, likely to be highly pronounced and fluctuating within individual wells. Consequently, performing spectral analysis on an entire well or even a whole formation may provide limited or even meaningless insights. Using small analysis windows as an alternative approach is not feasible since it results in poorly defined spectra when employing traditional Fourier-type methods. Instead, spectral estimation methods based on techniques such as maximum entropy (Childers, 1978) or wavelet transform are more suitable for analyzing well data. These methods account for the presence of discontinuities and changing spectral characteristics, making them more appropriate for extracting meaningful information from wireline logs.

If it is assumed that the geological record exhibits cyclic patterns influenced by climate change, then the possibility can be explored whether these cyclic properties provide insights into the continuity and discontinuity patterns present in the data. To achieve this mathematically, it becomes necessary to quantify spectral changes. Given that the spectra obtained through Maximum Entropy Spectral Analysis (MESA) rely on the calculation of prediction error filters (Childers, 1978), spectral changes by applying prediction error filtering to well log data can be quantified. This approach allows assessment of variation of the spectral properties and highlights the presence of changes in the data. By employing prediction error filtering in conjunction with MESA, effective investigation and quantification of spectral changes can be carried out which will provide valuable insights into the continuity and discontinuity patterns within the well log data.

Algorithm

Linear prediction of a data series involves creating the "best guess" for an unknown data point by combining known data points, accounting for noise in the data. This prediction can be applied either in the temporal domain, assuming some form of causality or recurring events, or in the spatial domain. In the context of well-log data, the prediction is typically performed in the depth domain, thus considered as spatial prediction.

In theory, a relationship between depth and geological time exists through the sedimentation rate. However, the sedimentation rate is highly dependent on the scale considered (Sadler, 1999) and cannot be determined with the necessary level of accuracy. The net accumulation rate, calculated by dividing the total thickness by the total elapsed time, is a crude approximation often used but does not provide a precise estimation. Therefore, in practice, the prediction of well-log data is performed based on available spatial information, acknowledging the limitations in accurately linking depth to geological time due to the scale-dependent nature of sedimentation rates.

The process of prediction can be modeled mathematically by using equation below.

$$y_n^* = \sum_{j=1}^{M} d_j y_{n-j}$$

The predicted data point,y_n^*, is obtained by linearly combining known data points, y_{n-j}, using weights, d_j. Optimal prediction aims to determine the optimal values for the prediction coefficients, d_j, which minimize the discrepancy between the known data, y_n, and the predicted data, y_n^*, for the set of data points to be predicted. This optimization process ensures that the predicted values closely match the actual values, achieving the best possible prediction accuracy.

In our specific case, the predictable portion of a dataset holds little significance, and it is the unpredictability that carries valuable information. Within the context of stratigraphic interpretation of well logs, the unpredictable component of the dataset is likely to be associated with depositional hiatuses. These unpredictable segments provide insights into periods of interrupted or non-depositional events, which are crucial for understanding the geological history and identifying potential gaps in the sedimentary record.

Implementation

To implement the algorithm, an executable code has been written on Python 3.7 environment. This program uses NumPy, CVXOPT library for matrix manipulation, Lasio and Pandas library for well log handling, Pywt library for wavelet transformation and MatPlotlib (Hunter, 2007) library for plotting purpose.

The algorithm is applied in the well of Panna Formation from Western Offshore Basin, India. The Panna Formation deposited during Late Paleocene to Early Eocene, having thickness ranges from 300-700m and non-conformably overlies the Deccan trap basalt/ Precambrian granitic gneiss Basement. Panna Formation is predominantly shale, occasionally sand and silt in association with carbonaceous shale/coal.

Spectral estimation from prediction coefficients:

The coefficients obtained from the optimal prediction of a data series are closely connected to the spectral properties of the underlying data. These prediction coefficients can be transformed into a spectral representation known as the maximum entropy spectrum. Consequently, variations in prediction coefficients correspond to changes in spectral content. Depth intervals exhibiting high unpredictability are likely to display anomalous spectral characteristics. By analyzing prediction errors, we can gain insights into spectral changes without the need for a comprehensive spectral analysis. This approach offers practical advantages as it is fast and enables interactive data analysis. It facilitates efficient and interactive exploration of the data, providing a valuable tool for identifying spectral changes and understanding the underlying geological processes.

Figure 1 presents an example of applying PEFA to a typical gamma-ray log. The method involves sliding a user-defined window (typically around 10 meters in

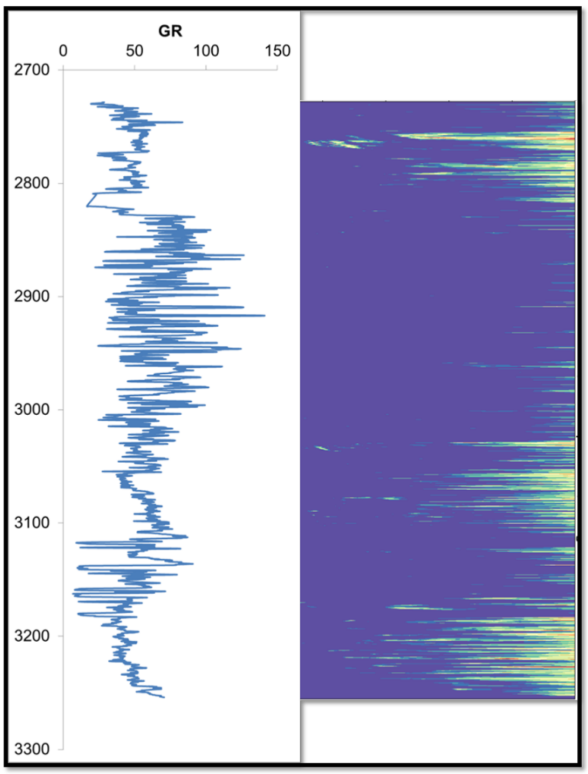

Figure 1: *Spectral change attribute analysis (PEFA) of the GR log, showing discontinuities in the spectral bands*

length) along the data, comparing the actual data with the prediction filter and calculating an error (positive or negative) at each depth. The outcome is an irregularly serrated curve that fluctuates around a straight vertical line. If a perfect prediction filter were possible (e.g., in the case of a perfectly regular waveform like a sine wave), the PEFA curve would be a straight vertical line. While quantitatively determining the magnitude of errors may be challenging, intervals with relatively small errors can be interpreted as "noise," suggesting limited discontinuity in the spectral properties from one window to the next. In contrast, larger spikes in the PEFA curve signify more pronounced discontinuities

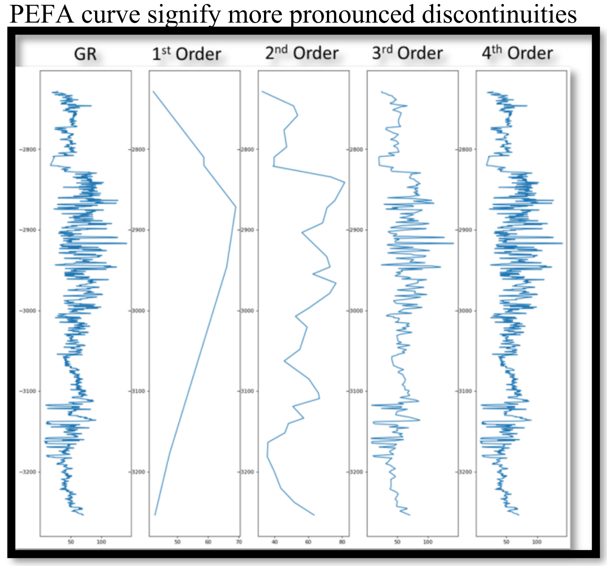

Figure 2: *As Figure 1 but with PEFAs of logs smoothed with median filters of four different orders*

in the spectral properties of the data. Such spikes often correspond to geological discontinuities of importance. For instance, in Figure 1, at a depth of 3123 meters, there is a major negative spike, indicating a significant overestimation of the gamma-

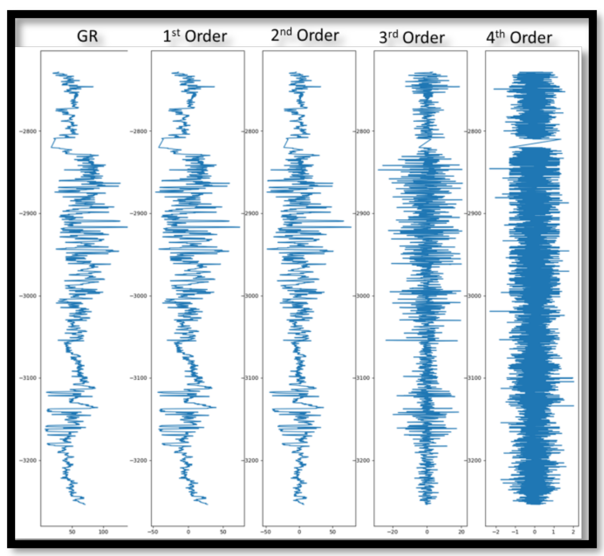

Figure 3: *Original GR log and PEFA curves derived from the smoothed logs of Figure 2*

ray (GR) value by the prediction filter. This suggests a sudden upward transition from shale to sand, potentially indicative of a sequence boundary. At a depth of 3067 meters, there is a significant positive spike, implying an underestimation of the GR value, which could be associated with a flooding surface characterized by a rapid increase in shalyness. These observations from the PEFA curve provide valuable geological insights, highlighting potential lithological or stratigraphic discontinuities that may have geological significance.

The interpretation of PEFA spikes described above can be subjective since it is common for geological successions to exhibit seemingly abrupt transitions between sand and shale. To distinguish between those transitions of local importance and those with broader regional significance, we employ a smoothing technique prior to applying PEFA. By smoothing the log, some of the less significant prediction errors are likely to be eliminated. Figure 2 depicts the same log as shown in Figure 1, but with three additional copies of the original gamma-ray (GR) log. Each of these copies has been smoothed using a median filter of progressively longer lengths. This approach allows us to assess the impact of different levels of smoothing on the PEFA results, aiding in the differentiation between significant and less significant prediction errors.

Figure 3 illustrates the resulting PEFA curves after applying the smoothing technique. It is evident that certain spikes observed in Figure 2 have been diminished to the level of "noise" through this process, while others remain prominent even after smoothing. Based on our interpretation, the spikes that persist after smoothing are likely to possess more regional significance compared to those that have vanished. This suggests that the persistent spikes indicate substantial and meaningful changes in the spectral properties of the data, potentially associated with broader geological features or transitions.

Analysis of Spectral Trend Attribute:

While the PEFA curve is valuable and innovative, its significance is overshadowed by the INPEFA curve. The transformation from the PEFA curve to the INPEFA curve is achieved through a straightforward mathematical integration process. Figure 4 presents an example of the resulting INPEFA curve.

The trends observed in the INPEFA curve emerge from the cumulative integration of the PEFA curve. When a segment of the data exhibits more frequent negative prediction errors, it will result in an overall negative (up-to-the-left) trend in the INPEFA curve. Conversely, if a segment of the data shows more frequent positive prediction errors, it will manifest as an overall positive (up-to-the-right) trend in the INPEFA curve. In the realm of stratigraphic data, smaller trends are often superimposed on larger ones. This means that an overall positive trend can contain intervals with a negative trend within it. The presence of these smaller trends adds complexity and richness to the INPEFA curve, enhancing our understanding of the stratigraphic patterns and variations within the geological succession.

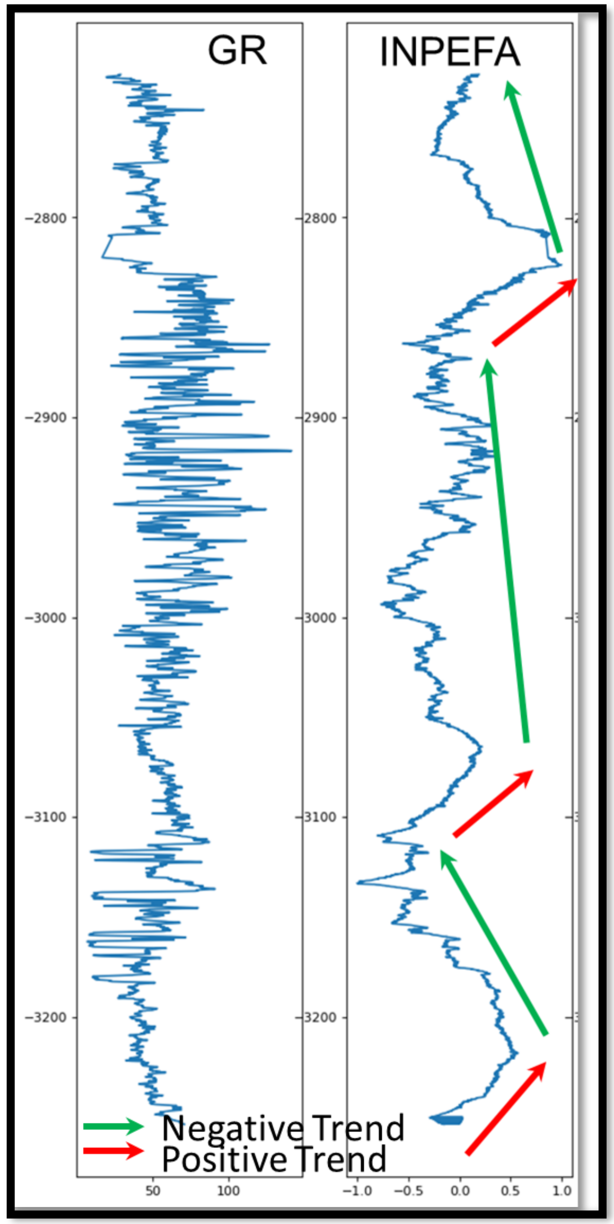

Figure 4: *Example of Spectral trend attribute analysis (INPEFA) of the GR log*

The primary features of the INPEFA curve, which we now examine for their significance, are the trends themselves and the turning points between them. These specific characteristics are uncovered by the INPEFA's spectral approach to the original data. The question arises: what is the geological significance of these identified trends and turning points? By analyzing the geological context and knowledge of the well logs, we can interpret the geological implications of these features. The trends observed in the INPEFA curve provide insights into the overall direction and changes in lithology, facies, or sedimentation patterns. Turning points indicate significant shifts or boundaries between different geological units, such as sequence boundaries, erosional surfaces, or depositional transitions. These features help us understand the geological processes, facies changes, and stratigraphic variations within the studied area. By leveraging the spectral approach of INPEFA, we can unlock valuable geological information and improve our interpretation of the wireline log data.

When the INPEFA curve exhibits a negative trend, it indicates a cumulative set of prediction error values that are predominantly negative. Negative prediction errors suggest an overestimation of the gamma-ray (GR) values by the filter. Thus, an overall negative trend in the INPEFA curve represents a segment of the data where the actual GR values are lower than predicted. In the context of a GR log, this implies that the actual values are more "sandy" than initially anticipated. In general terms, we can associate a negative INPEFA trend with a "regressive" pattern, although its exact geological significance depends on the specific context. For instance, a sanding-up trend could suggest factors such as (a) increased supply of coarse sediment, (b) shallowing-up conditions, or (c) decreasing distance from the shoreline. It is crucial to differentiate between the mathematical significance of the INPEFA trend, which is precise and objective, and its geological interpretation, which may involve more subjective analysis and contextual understanding.

In contrast, when the INPEFA curve demonstrates an overall positive trend, it signifies a segment of the data where the actual values of the log are higher than predicted. In the case of a gamma-ray (GR) log, this indicates that the actual values are more "shaly" than anticipated. In broad terms, a positive INPEFA trend can be associated with a "transgressive" pattern. This suggests potential geological implications such as (a) decreased sediment supply, (b) an increase in water depth or accommodation space, or (c) an increasing distance from the shoreline. However, the specific interpretation of the positive INPEFA trend depends on the geological context and must consider additional information and analysis.

Considering the geological significance of INPEFA trends, the turning points where these trends change, particularly when transitioning between positive and negative, hold crucial importance. The inflection points in the INPEFA curve have emerged as the most valuable aspect of this novel approach to log data analysis. They provide key insights into significant shifts and boundaries within the geological interpretation. By examining these turning points, we can identify critical geological features such as sequence boundaries, erosional surfaces, or abrupt changes in lithology or facies. Thus, the turning points in the INPEFA curve offer valuable information that enhances our understanding of the geological characteristics and evolution of the studied area.

At the turning point where, for example, an overall negative (sanding-up/ coarsening up) trend transitions to an overall positive (shaling-up/fining up) trend in the INPEFA curve, we can confidently infer that a significant change has influenced the depositional system. This shift suggests that the supply of sand has been abruptly halted, possibly due to a change in base-level, which could be associated with climatic changes or other geological factors. Conversely, at the opposite turning point from positive to negative, we observe the reverse effect, indicating a sudden resumption of deposition of sandier sediments. These turning points highlight abrupt changes in sedimentation patterns and provide valuable evidence of significant shifts in the depositional environment, shedding light on the dynamic interplay between geological processes and potential external factors such as climate change.

Assuming our initial assumption holds true, which is that orbitally-forced climatic changes have a detectable impact on depositional facies, it is highly probable that certain turning points in the INPEFA curve correspond to significant shifts in the depositional regime triggered by climate change. It is important to note that we utilize spectral methods to generate the PEFA and INPEFA transforms, relying on the inherent waveforms within the original log data. If these changes are indeed influenced by climate change, they are likely to occur synchronously on a regional scale within a particular climatic belt. This significant finding forms the basis for subdividing INPEFA curves into cyclic units and enables their correlation between different wells. However, it is essential to recognize that climatic change within the Milankovitch waveband is limited to periodicities in the range of 102 to 103 thousand years (ka). Thus, orbitally-forced climatic change cannot account for features in the INPEFA curve representing longer time periods. Instead, we may be observing the interplay of longer-term tectonic changes with shorter-term climatic cyclicity superimposed upon them. This suggests that multiple factors, including both tectonic and climatic influences, contribute to the observed patterns in the INPEFA curves over various timescales.

Conclusion:

The PEFA and INPEFA curves provide valuable insights that would otherwise remain concealed in untreated logs. The PEFA curve exposes discontinuities in the spectral properties of the logs, shedding light on their presence and providing information about their relative magnitude. On the other hand, the INPEFA curve reveals distinctive trends within the data, delineated by turning points that can be interpreted as significant events in the depositional history of the basin at a regional scale. This approach unlocks previously hidden information and enriches our understanding of the geological processes and dynamics recorded in the wireline log data.

At the core of this concept lies the assumption that suitable facies-sensitive logs can serve as a reliable proxy for capturing the effects of Milankovitch-scale climate change as manifested in sedimentary strata. By treating wireline logs as "time-series" data in an analytical sense, albeit not strictly in a geological sense, spectral methods can be applied that pave the way for the development of PEFA and INPEFA. In this paper, the examples predominantly utilize the natural gamma-ray (GR) log, which is commonly included in routine log suites. The GR log offers several advantages, including its widespread availability, relatively low sensitivity to hole conditions, and its ability to provide a reasonable representation of the depositional environment, particularly in clastic systems. It is important to note that the interpretation of other logs or the GR log in carbonate settings may exhibit some differences compared to the examples presented in this paper. These variations arise due to the distinct characteristics and responses of different logging measurements in various lithology and depositional environments. Thus, while the GR log remains a valuable and widely applicable tool, additional considerations and adjustments may be necessary when interpreting other logs or when dealing with carbonate reservoirs.

The approach of INPEFA analysis bears similarities to sequence stratigraphy. Key bounding surfaces with temporal significance can be identified, which separate intervals that may exhibit distinct characteristics. This methodology offers higher resolution compared to what is typically achievable in seismic data analysis. Further research is required to establish a more detailed understanding of the relationship between the key surfaces identified in seismic stratigraphy; those revealed through INPEFA analysis and automated correlation technique.

Acknowledgement:

Authors are thankful to ONGC management for permitting to publish the work. The views expressed in the paper are those of the authors only. The authors are indebted to Shri J.P.G Dobriyal, CGM-HOI GEOPIC and Shri Kishori Lal, CGM-Head INTEG-GEOPIC and Shri S.S Dash, DGM (Geology) for according permission, providing infrastructural facilities, continuous guidance and inspiration in the study.

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