Spectral Trend Attribute Analysis: Applications in the Stratigraphic Analysis of Wireline Logs

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Spectral trend attribute analysis: applications in the stratigraphic analysis of wireline logs

S. Djin Nio[1], Jan Brouwer[3], David Smith[2], Mat de Jong[1], and Alain Böhm[1] present what they claim to be an entirely new methodology for the stratigraphic interpretation of wireline logs.

We describe a new analytical tool - Spectral trend attribute analysis – and its application in the interpretation of wireline log data. A typical well log comprises a series of values of some property, normally taken at regularly spaced depth intervals. As such it can be treated as a (depth-) time-series for the purposes of mathematical analysis. Using all or a selected part of a facies-sensitive log such as the natural gamma-ray (GR) log, we compute a prediction error filter. The filter is chosen to predict new data samples from preceding samples. The filter is used to calculate a new data-series, each point of which is the numerical error between the predicted and actual value at the corresponding depth. The resulting prediction error filter analysis (PEFA) curve can be interpreted geologically as an indicator of the continuity or otherwise of the stratigraphic succession - larger errors imply more significant breaks in the succession. When numerically integrated, the PEFA curve yields a still more valuable curve - the INPEFA (Integrated PEFA) curve - which reveals trends and other patterns that are not generally apparent from the original log data. The INPEFA curve leads directly to a method for the objective subdivision of geological successions by the identification of key surfaces, somewhat analogous to the 'sequence' analysis of seismic profiles. We outline the basic principles of spectral trend attribute analysis, and stress the universality of its applicability to routine stratigraphic analysis of well logs.

Introduction

Wireline log data represent a vast repository of quantitative information about subsurface geology. Whereas their application in petrophysics and in the calibration of seismic data is necessarily quantitative, geological applications are conventionally more qualitative (Rider, 1996). The scope for a more quantitative approach to the geological interpretation of log data is enormous; we here describe such an application, with direct bearing on the stratigraphic interpretation of well logs.

The vast majority of well logs comprise (after optional resampling) regularly spaced readings of some physical quantity such as resistivity. Whereas earlier wireline logs were recorded in analogue form and thus appear as continuous traces, modern logs are recorded digitally, with data-points at discrete intervals. A log being a series of values at regularly spaced increments, it is immediately amenable to all the techniques of 'time-series' analysis, including the spectral (frequency) methods that are the subject of this paper.

From the basic principle of superposition, it is generally (though not universally) true that the deeper a borehole penetrates, the older are the strata encountered. However, geological age does not increase uniformly with depth, for two reasons: (1) rates of deposition are highly variable; and (2) deposition is a highly discontinuous process at any one location (Sadler, 1999). A series of data-points sampled at regular intervals down a borehole is therefore regular only in depth. (It may be regular in terms of *sampling* time, if the logging tool is drawn at uniform speed up the borehole, but this is not geologically interesting). However, it is anything but regular in terms of *geological* time. In practice, geologists are accustomed to working within this limitation of their basic data, which applies just as much at outcrop as in the subsurface. More important is the question of whether this invalidates the application of classical 'time-series' methods to the *geological* interpretation of wireline log data. We do not believe so, and we invite the reader to judge our approach by its results.

The origin of our use of spectral methods comes from our interest in the detection of Milankovitch rhythms in stratigraphic data. Orbitally forced climate changes are predicted to be recorded in strata, because of the likely influence of varying insolation on mechanisms of erosion, transport and deposition. Verification of this prediction over recent decades (Schwarzacher, 1993; Weedon, 2003) opens up the possibility of the identification of individual climate cycles and their use in high resolution correlation. Since the predicted Milankovitch periods fall in the range of tens to hundreds of thousands of years, considerable improvements in resolution are theoretically possible, compared with the conventional methods of biostratigraphy and seismic stratigraphy. The possibility that Milankovitch cycles might be detectable in wireline logs led us to develop specialized software for the spectral analysis of logs.

A problem with applying spectral methods such as Fourier Analysis to geological 'time-series' data is the cer-

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tainty that there are significant (but unknowable) discontinuities and other changes in the properties of the data, as outlined above. The spectral properties of wireline logs are therefore likely to change, probably very considerably, through any individual well. Even within a single geological unit such as a formation, discontinuities are to be expected. Thus, *spectral analysis* of an entire well, or even of a whole formation, may be rather uninformative and indeed meaningless. Using small windows of analysis is not a viable alternative, as it results in poorly defined spectra when traditional (Fourier type) methods are applied. *Spectral estimation* based on, for example, maximum entropy (Childers, 1978) or wavelet transform methods, is the more appropriate approach for application to well data.

Assuming that the record is characterized by cyclic patterns imposed by climate change, can we use these cyclic properties to investigate the patterns of continuity versus discontinuity in the data? Mathematically, this requires quantification of *spectral change*. Although this could be performed through the comparison of the spectral characteristics of successive windows of analysis (e.g. first and second order moments calculated from the respective spectra) we have developed a different approach. Since spectra determined through MESA are based on the calculation of prediction error filters (Childers, 1978), quantification of spectral change may be implemented through the application of prediction error filtering to our well log data.

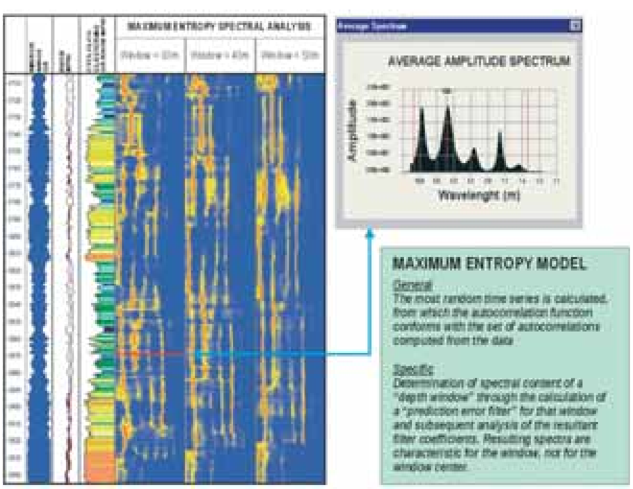

Figure 1 *Example of Maximum Entropy Spectral Analysis (MESA) of the GR log with three different analysis window sizes. Permian Rotliegend interval, Netherlands Offshore (courtesy NITG-TNO).*

Linear prediction of time (depth) series

Linear prediction of data series involves the construction of a 'best guess' of the value of an unknown data-point through the linear combination of known, but noisy data-points. Prediction could be either in time (assuming some sort of causality, or recurring events) or in space. In practice, prediction of well-log data takes place in the depth domain and should thus be regarded as spatial prediction. In theory, a link between depth and geological time is provided by sedimentation rate, but this is a highly scale-dependent quantity (Sadler 1999) and it cannot be determined to the required level of accuracy. Net accumulation rate (total thickness divided by total elapsed time) is a poor approximation but is generally all that is available.

The prediction process can be mathematically described by equation (1).

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

Here y_n* is the data point predicted from the linear combination of known data points y_{n-j} through weighting with d_j. Optimal prediction involves the selection of the individual weights d_j (the prediction coefficients) such that the discrepancy between known y_n and predicted y_n* is minimized (in some optimal sense) for the set of data-points that are to be predicted.

In our case, the predictable part of a dataset is rather uninteresting, and it is the unpredictability that represents valuable information. In the context of stratigraphic interpretation of well logs the unpredictable part of the data set can be expected to relate to depositional hiatuses.

Spectral estimation from prediction coefficients

The coefficients found for the optimal prediction of a data series are closely related to the spectral content of the underlying data. In fact the prediction coefficients can be easily transformed into a spectral representation of the data known as the maximum entropy spectrum. Changes in prediction coefficients thus relate to changes in spectral content and depth ranges that appear as highly unpredictable will most probably be anomalous in their spectral characteristics. Prediction error analysis can thus give an indication of spectral change without the necessity to perform a full spectral analysis. This makes it very fast in its practical application, allowing a high degree of interactivity when analyzing data.

We turn now to the geological interpretation of the results of prediction error filter analysis (PEFA). An example of the application of PEFA to a typical gamma-ray log is shown in Figure 2. The effect of the method is to move a window of user-defined length (typically in the order of 10 m) up the data, comparing the actual data with the filter, and scoring an error (positive or negative) at each depth. The result is an irregularly serrated curve, varying about a straight vertical line. If it were possible to compute a perfect prediction filter (for example, if the log were a perfectly regular waveform such as a sine wave), the PEFA curve would be a straight vertical line. Although we hesitate to put quantitative confidence limits on the magnitude of the errors, it is reasonable to interpret intervals of rather small errors as 'noise', implying that there is relatively little discontinuity in the spectral properties of the data from one window to the next. Where there are larger 'spikes' in the PEFA curve, we can infer that there is a more or less significant discontinuity in the spectral properties of the data. This in turn may imply a discontinuity of geological significance. For example, in Figure 2 at 3980 m there is a major negative spike, implying that the GR value at that depth has been significantly over-estimated by the prediction filter. This implies a sudden upward transition from shale to sand, the degree of discontinuity possibly implying that this could be a candidate location for a sequence boundary. At 3965 m there is a major positive spike, implying under-estimation of the GR value, which could be a candidate for a flooding surface as it represents a relatively sudden upward increase in shaliness.

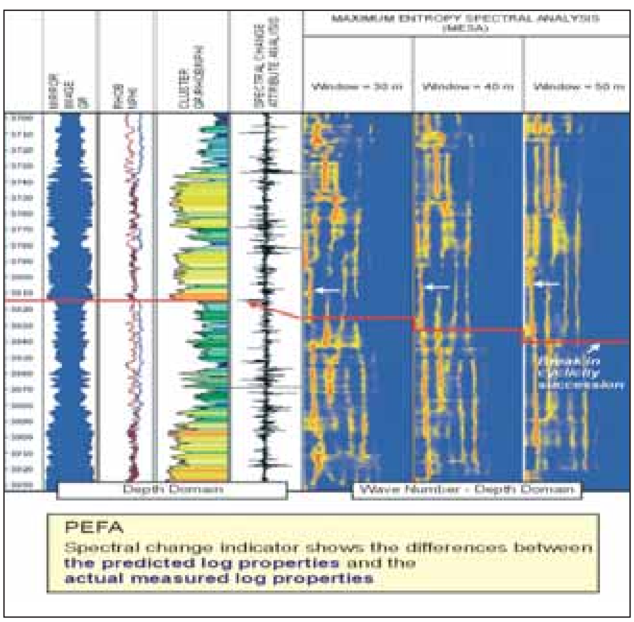

Figure 2 *Spectral change attribute analysis (PEFA) of the GR log, showing discontinuities in the spectral bands as shown as negative peaks (to the left) and positive peaks (to the right). These peaks represent breaks in the cycle successions and can be interpreted as major or minor stratigraphic breaks.*

The above interpretation of PEFA spikes is rather subjective, as it is quite normal for a geological succession to comprise many apparently sudden switches between sand and shale. We attempt to differentiate between those of local and more regional significance as follows. If the log is smoothed before using PEFA, then some of the less significant prediction errors are likely to disappear. Figure 3 shows the same log as Figure 2, with three copies of the original GR log, each smoothed with a median filter of successively longer length. The resulting PEFA curves are shown in Figure 4. Notice how some of the spikes in Figure 2 have been reduced to the level of 'noise' by this process, whereas others persist through the smoothing operation. Our interpretation is that the more persistent spikes are likely to have more regional significance than those that have disappeared.

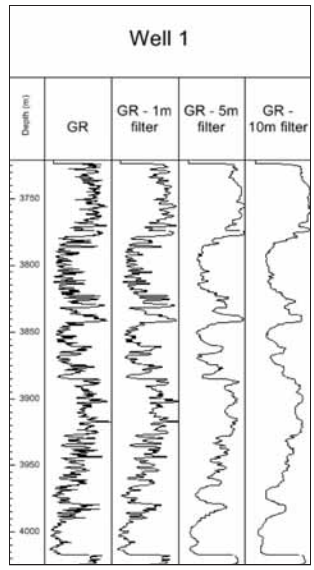

Figure 3 *As Figure 2 but with PEFAs of logs smoothed with median filters of three different lengths (1 m, 5 m and 10 m).*

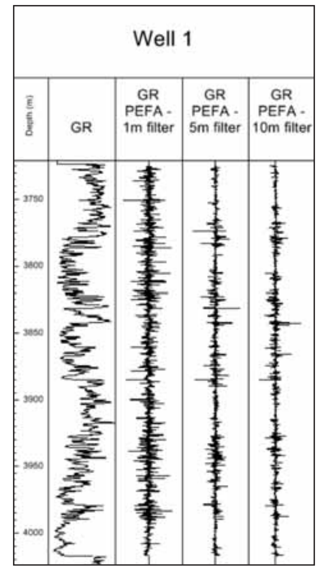

Figure 4 *Original GR log and PEFA curves derived from the smoothed logs of Figure 3.*

Spectral trend attribute analysis – the INPEFA curve and its interpretation

Useful and novel as the PEFA curve is, its value is eclipsed by that of the INPEFA curve. The PEFA curve is transformed into the INPEFA in one step, by simple mathematical integration. An example of the result is shown in Figure 5. Note that we routinely display the INPEFA curve in a wider track than other logs, because its significance lies in the trends that are added to the variance of the raw log data.

The trends revealed by INPEFA result from the cumulative effect of integrating the PEFA curve. A segment of the data in which the prediction errors are more often negative will have an overall negative (up-to-the-left) trend. A segment of the data in which the errors are more often positive will have an overall positive (up-to-the-right) trend. As in so many aspects of stratigraphic data, smaller trends are superimposed on larger ones; an overall positive trend will have intervals with negative trend within it.

The key features of the INPEFA curve whose significance we now consider are the trends themselves, and the turning-points between them. These are the specific features that INPEFA reveals through its spectral approach to the original data; what (if any) is their geological significance?

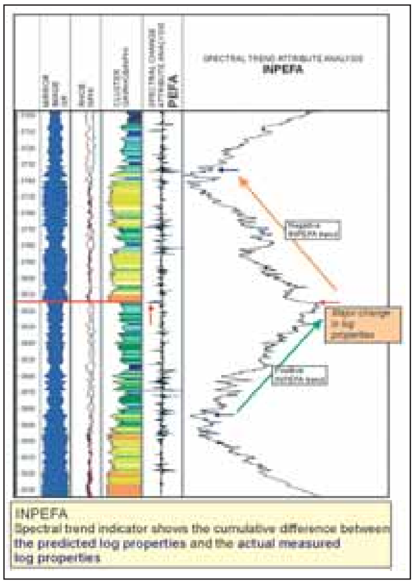

Figure 5 *Example of Spectral trend attribute analysis (INPEFA) of the GR log (same well as in Figure 1 and 2). See text for explanation (courtesy NITG-TNO).*

A negative INPEFA trend results from a cumulatively negative set of prediction error values. Negative prediction error values imply over-estimation of the GR value by the filter. Therefore, an overall negative trend in the INPEFA curve represents a segment of the data through which the actual values of the log are less than predicted. In the case of a GR log, the actual values are more 'sandy' than predicted. In very general terms, we can therefore think of a negative INPEFA trend as 'regressive', although its exact significance will be dependent on the geological context. A sanding-up trend could, for example, imply (a) increased supply of coarse sediment, (b) shallowing-up, or (c) decreasing distance from shoreline. We have to be careful to distinguish between the mathematical significance of the INPEFA trend, which is precise and objective, and its geological interpretation, which may be more subjective.

Conversely, an overall positive trend in the INPEFA represents a segment of the data through which the actual values of the log are greater than predicted. For a GR log, this means that the actual values are more 'shaley' than predicted, implying (in general terms again) a 'transgressive' trend. This might represent (a) decreased sediment supply, (b) increase in water depth or accommodation space, or (c) increasing distance from shoreline, depending on context.

Given the geological significance of INPEFA trends, the points at which the trends change, especially where they change between positive and negative, should also be important. These *turning-points* in the INPEFA curve have proved to be perhaps the most valuable feature of this new approach to log data.

At the turning-point where, say an overall negative (sanding-up) trend gives way to an overall positive (shaling-up) trend, we can be sure that some significant change has affected the depositional system. The sand supply has been 'switched off', possibly through a change in base-level, which in turn may be linked to a climatic change. At the opposite turning-point, from positive to negative, the reverse effect has taken place and there is an abrupt resumption of sandier sediment deposition.

Assuming that we are correct in the assumption we made at the outset - that orbitally-forced climatic change has a detectable influence on depositional facies - then it is very likely that *some* INPEFA turning-points represent significant changes in the depositional regime brought about by climate change. (Recall that we are using spectral methods to generate the PEFA and INPEFA transforms, and that such methods depend on the waveforms inherent in the original log data.) This being so, those changes are likely to be synchronous on a regional scale (and within a climatic belt). This important con-

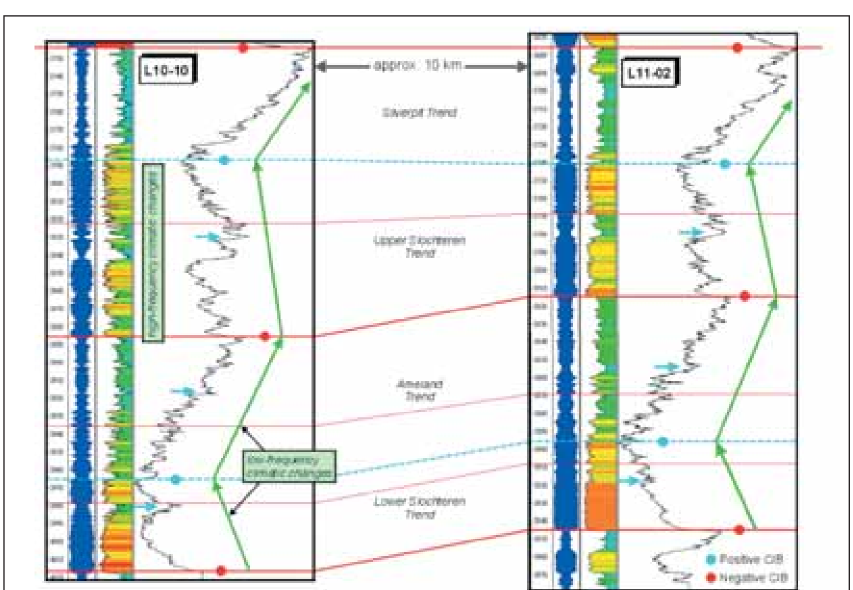

Figure 6 *Example of two-well correlation to illustrate hierarchical approach to INPEFA analysis. Solid red lines represent cycle boundaries, picked at positive-to-negative turning points; dashed blue lines are 'termination surfaces', picked at negative-to-positive turning points. Thicker red lines bound 'master' cycles; thinner red lines bound higher order 'slave' cycles.*

clusion is the basis for the subdivision of INPEFA curves into a hierarchy of cyclic units, and their correlation between wells. Note, however, that climatic change in the Milankovitch waveband is limited to periodicities in the order of 10^2 to 10^3 ka. Orbitally-forced climatic change cannot therefore be invoked for features of the INPEFA curve representing longer periods of time, and it is likely that we are looking at the interaction of longer period tectonic change, with shorter period climatic cyclicity superimposed upon it.

The above arguments suggest that a hierarchical approach to the stratigraphic analysis of the INPEFA transform is an appropriate way to proceed. Detailed examples of analysis are beyond the scope of this paper, but we end by illustrating the concept with a simple two-well correlation using a stratigraphic breakdown based on the INPEFA curve. Figure 6 illustrates the hierarchical approach by using thicker lines to represent the main or 'master' cycle boundaries that we identify in this example, with thinner lines to represent the higher-order 'slave' cycles. The inference that the turning-points represent regionally significant events is the justification for using the INPEFA curves to generate a stratigraphic framework that can be assumed to be time-significant.

Conclusions

Through investigation of the spectral properties of wireline log data, we have discovered and developed an entirely new methodology for the stratigraphic interpretation of logs. The PEFA and INPEFA curves yield information that is otherwise largely hidden in untreated logs. The PEFA curve reveals breaks in the continuity of the spectral properties of the logs, and gives useful information about the relative magnitude of those breaks. The INPEFA curve reveals trends in the data, separated by turning-points that can be interpreted as regionally significant events in the depositional history of the basin.

Underlying these discoveries is the assumption that appropriate (facies-sensitive) logs can provide a good proxy for the effects of Milankovitch-scale climate change as recorded in sedimentary strata. Treating the wireline logs as 'time-series' (in an analytical sense though not in a strict geological sense) allows the application of the spectral methods that lead to PEFA and INPEFA. The examples in this paper all use the natural gamma-ray (GR) log, which is widely available in routine log suites, is relatively insensitive to hole conditions, and (most importantly) is generally a good proxy for depositional environment, in clastic systems at least. Interpretation of other logs, or of the GR log in carbonates, may differ somewhat from the examples shown here.

The approach to INPEFA analysis that we advocate here has parallels with sequence stratigraphy; we identify key bounding surfaces, with time significance, which separate intervals that may be of distinctive character. Because it is notoriously difficult to pick seismically defined sequence boundaries and maximum flooding surfaces in well logs, we do not draw a direct parallel between these surfaces and our INPEFA turning points. Our approach, on the other hand, allows a more objective subdivision of well logs into time-significant and correlatable units, and at a higher resolution, than is possible in seismic data. Further work will be needed to establish in more detail the relationship between the key surfaces of seismic stratigraphy and those revealed by INPEFA.

Acknowledgement

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References

Childers, D.G. (Ed.) [1978] *Modern Spectrum Analysis.* IEEE Press, New York.

Press, W.H., Flannery, B.P., Teukolsky, S.A., and Vetterling, W.T. [1988] *Numerical Recipes in C, The Art of Scientific Computing.* Cambridge University Press.

Rider, M.H. [1996] *The Geological Interpretation of Wireline Logs*, 2nd Edition. Whittles Publishing, Scotland.

Robinson and Treitel [1980] *Geophysical Signal Analysis*, Prentice-Hall, Englewood Cliffs.

Sadler, P. M. [1999] The influence of hiatuses on sediment accumulation rates. In Bruns, P. and Hass, H. C. (eds.): On the Determination of Sediment Accumulation Rates. *GeoResearch Forum*, **5**, 15-40, Trans Tech Publications, Switzerland.

Schwarzacher, W. [1993] Cyclostratigraphy and the Milankovitch Theory. *Developments in Sedimentology 52*. Elsevier.

Silvia and Robinson, [1979] *Deconvolution of Geophysical Time Series in the Exploration for Oil and Natural Gas*, Elsevier, Amsterdam.

Weedon, G.P. [2003] *Time-Series Analysis and Cyclostratigraphy.* Cambridge University Press.