Well Log Vertical Resolution Enhancement by Recurrent Neural Network.

Aldenize de Lima Ruéla*, Anna Ilcéa Fischetti e André Andrade, UFPA/CG/ProLog

This paper was prepared for presentation at the 9th International Congress of the Brazilian Geophysical Society held in Salvador, Brazil, 11-14 September 2005.

Abstract

The reevaluation of mature or small oil fields, where there are only conventional well log data or the use of new logging technologies have not economic viability motivate us to take a new look in log vertical resolution enhancement. We talk about the paradox between depth of investigation and the vertical resolution of a logging tool.

This work aims to improve the vertical resolution and keep the depth of investigation unchanged by the development of an iterative block processing based on recurrent neural networks. From the convolutional well log model we introduce a method to smoothing the linear disturbances introduced by the tool in the well log and improve the log vertical resolution. The block processing is based on three recurrent neural network architectures. The first one seeks to estimate the vertical tool response; the second one tries to determine the vertical limits of layers and the last one is constructed to estimate the actual physical property.

The efficiency and limitations of this methodology are exemplified with one gamma ray log from a well drilled in Namorado oil field, Campos basin, Brazil.

Introduction

For oil industry, wireline logging is the major technique to infer the occurrence and evaluate hydrocarbon bearing rocks. It is done by the measure and interpretation of physical properties of rocks surrounding the borehole. These measures are acquired by a logging tool containing one or several sensors that is pulled up hole on a cable. The signal obtained in each measure point can be considered as a weight average of the physical property on the whole rock volume investigated by the logging tool (Ellis, 1987). Thus, the logging tool contaminates the value of a rock physical property, in a measure point, with undesirable information from its neighborhood.

Well log can be modeled by a convolution operation between the vertical variation of rock physical property (ideal log) and a function that describes the blurring caused by the logging tool in this property (vertical tool response). One way to improve the log vertical resolution is to use the convolution inverse operation – The deconvolution. As we talk about linear operations, only this kind of events may be removed from actual well logs.

Some authors try to solve these kind of problems with different methodologies: statistical methods (Nosal, 1983; Flexa and others, 2001), digital filters and Fourier transform (Barber, 1988; Andrade & Luthi, 1993), artificial intelligence (Baldwin and others, 1989) and Hopfield neural network (Andrade and others, 1995). Many papers have been published showing the applicability of artificial neural networks in the oil industry, involved in a larger class of intelligent algorithms, e.g. soft computing (Nikravesh, 2004) and interpretative algorithms (Fischetti & Andrade, 2002).

In the sense of artificial neural networks we present one association between the energy function, related to recurrent neural networks and the object function of error minimization, related to well log deconvolution problem. So, the decreasing behavior of the energy function produced by network dynamic is associated with the minimization of error function. Using recurrent neural networks, the error function partial derivates are avoided and we show that limitation of energy function local minimization does not introduce additional problems in this application.

We develop an iterative block processing composed by three recurrent neural networks. The first one looks for an improvement in the estimative of vertical tool response; this result makes possible the next two steps. In the second neural network, we establish the subsurface disposition of each rock layer, with the identification of its interfaces (top and bottom of layer). In the last one, we establish the tool effect attenuation on the rock physical property magnitude.

The final results show improvements in the log vertical resolution and in the physical property evaluation, with improvement of signal/noise ratio and in the time processing of well log data.

The efficiency and limitations of this methodology are evaluated with synthetic logs and actual natural gamma ray log (GR) from Namorado oil field, Campos basin, Brazil.

Recurrent neural network

Recurrent neural network is a special class of unsupervised artificial neural networks. It is composed by only one layer of recurrent neurons, which after an initial input signal produces an output signal that is send back, as new input signal, for all neurons in the recurrent layer (Figure 1). This dynamic process is controlled by a decreasing behavior of an energy function, which depends on the states of recurrent neurons in each time step. Thus, a network stable state corresponds to a local minimum of energy function (Hopfield, 1982). In this characteristic resides the interest in the use of a recurrent neural network to solve an optimization problem. If we can associate a problem dependent cost function with the energy function, when the recurrent neural network reaches its stable state, the outputs of the network give the solution of the optimization problem.

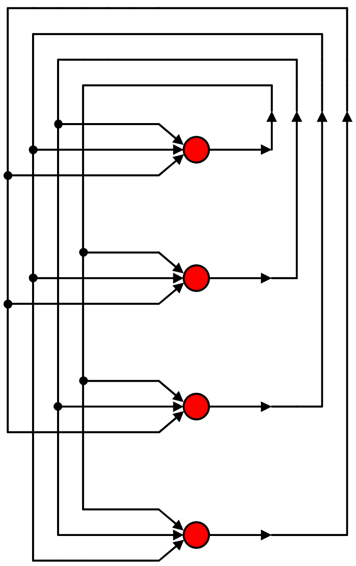

Figure 1: Recurrent neural network architecture.

To build a recurrent neural network, we define the input potential P_k to the neuron k as

$$P_k(t) = \sum_{i=1}^{N} w_{ki} v_i(t) , \quad (1)$$

where v_i represents the state (output signal) of neuron i in the time t and w_{ki} is the synaptic weights that represents the connections to neuron k of all other neurons. The matrix W has the following properties: $w_{ki} = w_{ik}$ and $w_{kk} \geq 0$, showed here without proof.

The input potential represents the influence of all other neurons in the neuron k output. Under this point of view, the expression "potential" refers only the capacity of a neuron to produce an effective output (non zero) signal.

We take as recurrent neuron activation function the following expression

$$\mathrm{v_k(t) = f[P_k(t-1)]} = \begin{cases} 1, & \mathrm{se\ P_k(t-1) \geq I_k} \\ 0, & \mathrm{se\ P_k(t-1) < I_k} \end{cases} . \quad (2)$$

This formulation for the activation function $(f[P_k(t)])$ differs from that one adopted in the Hopfield neural network, due the presence of parameter I_k, designated as external input, which determines the new neuron state (v_k) in the time t, as shown in Figure 2.

We adopt as energy function a variation form of classical recurrent neural network, written as

$$E = -\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} v_i v_j + 2\sum_{i=1}^{N} I_i v_i . \quad (3)$$

The energy function variation ΔE associated with the network dynamic, due the state change of only one neuron in each time instant, is always smaller or equal to zero, assuring the convergence to a local minimum of energy function.

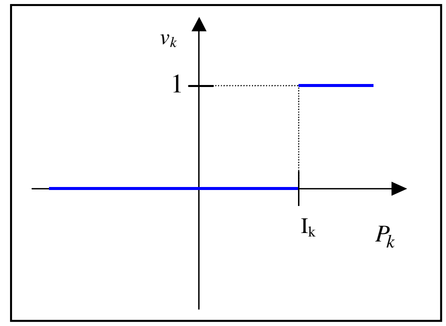

Figure 2. Recurrent neural network activation function.

Log convolutional model

We describe a well log by the convolutional model, in the following form

$$y_k = \sum_{k=1}^{N} p_{k-i} g_i \quad (i = 1, 2, 3, ..., N) , \quad (4)$$

where y_k represents the log readings, p_k is the physical property distribution, considered constant in each infinitesimal element of rock volume investigated by the logging tool, and g_k is the vertical tool response.

Methodology

The fundamental premise adopted here is the association between the network energy function and an error function, characteristic of the problem. Through this association the matrix of synaptic weights and the vector of external inputs are determined and will be used in the recurrent neural network to improve the log vertical resolution.

The goal here is to solve the expression (4) in the sense of its inverse operation. So, we want to find the actual values for p_k, but we do not know the g_k values. To overcome this indetermination and to start the process, we supply a first guess about the ideal log, which may be weakly related to actual log and will be used to provide an external estimative of vertical tool response. We take two approaches: (1) the boxcar log and (2) a well log with higher vertical resolution than the one we are processing. We discuss each case separately, in the next paragraphs.

The assumption of homogeneous material (lithology) in each rock layer, admitted in the convolutional model, induced the association of the ideal log with the boxcar function, originating the boxcar log or a synthetic log that exhibits a uniform value for the physical property in each rock layer. The algorithm that constructs the boxcar log is based on a move average and a threshold. To decide if a depth point belongs to a given layer, the difference between the arithmetic medians of actual log readings, including and excluding this particular point is compared to a threshold. If the difference is less than threshold, the point belongs to this layer, if opposite occurs, an interface is reached. The boxcar log is built analyzing each point in the well log. If the boxcar log is constructed from a noise free synthetic log it may be very close to this log, but when actual well log is used, a weakly relation may exist between the boxcar log and the in depth variation of rock physical property.

In the second case, we can use as a first guess about the ideal log another well log, with higher vertical resolution than processed one, measured in the same depth interval, to take advantage of its better interface definition. In both case, they have the same role in the block processing, which is to start the process.

In a complex geological setting, the boxcar log produces a hard restriction requiring a homogeneous rock and the log with high resolution may be more appropriated to get more reliable interfaces positions.

In the next sections, we show how the free parameters of each neural network are obtained to operate in the block processing until a specified error goal to be reached.

The vertical tool response estimative

The characteristic error function is taken as the error minimization function, which is represented by the sum of squared errors, given as

$$E=\frac{1}{2}\sum_{k=1}^{N}\left(y_k-y'_k\right)^2 \quad , \tag{5}$$

where y'_k is the log obtained by the convolutional model showed in the expression (4) and y_k is the measured well log. Assuming $g_i \neq 0$ and $p_i \neq 0 \quad \forall \quad i > 0$, in expression (4), the expression (5) can be rewritten as

$$E=\frac{1}{2}\sum_{k=1}^{N}\left(y_k-\sum_{i=1}^{N}p_{k-i}g_i\right)^2 . \tag{6}$$

The vertical tool response is obtained in two stages. The first one is the acquisition of its external estimative $\left(g_i^{ext}\right)$ based on the concept of point spread function (PSF) (Andrade & Luthi, 1993). The recurrent neural network is constructed to obtain a correction for g^{ext} as output. Thus, the vertical tool response (g^{rec}) is written as

$$g^{rec}=\left(1+g'_i\right)g_i^{ext} . \tag{7}$$

The term g'_i can be normalized to $\left|g'_i\right|\leq 1$, acting as a weight correction of external estimative of vertical tool response (g_i^{est}) and expressed by,

$$g'_i=\left(\sum_{j=1}^{M}\frac{1}{2^{j-1}}x_{ij}\right), \tag{8}$$

where x_{ij} assumes values in {0, 1}. The expression (8) can be understood as a binary vector decoding with *M* bits.

Substituting the expression (7) in the expression (6), and ignoring the terms not depend on x_{ij}, we have for the energy function, the following expression

$$E=-\sum_{k=1}^{N}\left[\sum_{i=1}^{N}p_{k-i}\sum_{j=1}^{N}\frac{1}{2^{j-1}}\left(y_k-\sum_{i=1}^{N}g_i^{ext}p_{k-i}\right)g_i^{ext}\right]x_{ij}+$$
$$\frac{1}{8}\sum_{k=1}^{N}\sum_{i_1=1}^{N}\sum_{i_2=1}^{N}\sum_{j_2=1}^{M}\sum_{j_1=1}^{M}g_{i_1}^{ext}g_{i_2}^{ext}\frac{1}{2^{j_1-1}}\frac{1}{2^{j_2-1}}x_{i_1j_1}x_{i_2j_2} \tag{9}$$

Associating the equation (9) with equation (3), we have the network synaptic weight matrix, given by

$$w_{i_1i_2j_1j_2}=\frac{1}{8}\sum_{k=1}^{N}p_{k-i_1}p_{k-i_2}\frac{1}{2^{j_1-1}}\frac{1}{2^{j_2-1}}g_{i_1}^{ext}g_{i_2}^{ext} \tag{10}$$

and the external input vector as

$$I_j=-\frac{1}{4}\sum_{k=1}^{N}\sum_{i=1}^{N}p_{k-i}\frac{1}{2^{j-1}}\left(y_k-\sum_{i=1}^{N}g_i^{ext}p_{k-i}\right)g_i^{ext} . \tag{11}$$

Here, the time serie that describes the vertical tool response does not have any physical meaning, being just a processing element, necessary to start the block processing.

The interface identification

To identify the presence of an interface, we rewrite the sequence p_i, in the expression (4) as

$$p_i=c_i+r_i\left(\frac{c_{i-1}+c_{i+1}}{2}-c_i\right), \tag{12}$$

where c_i represents the physical property value in the layer i. The sequence $r_i \in$ {0,1} can be deterministic or aleatory, in a way that if $r_i=1$, we meet an interface with amplitude given by $\frac{c_{i-1}+c_{i+1}}{2}$ and if $r_i=0$, we meet a layer considered homogeneous and isotropic, presenting a constant physical property with amplitude equal to c_i.

Substituting in the expression (6) the value of p_i supplied for the expression (12) and ignoring the terms not depending of r_i, we obtain the cost function expressed by

$$E=-\sum_{k=1}^{N}\sum_{i=1}^{N}\left(y_k-\sum_{j=1}^{N}c_jg_{k-j}\right)h_ig_{k-i}r_i+$$
$$+\frac{1}{2}\sum_{k=1}^{N}\sum_{i=1}^{N}\sum_{j=1}^{N}h_ih_jg_{k-i}g_{k-j}r_ir_j \quad , \tag{13}$$

where the terms h_i and h_j are written as

$$h_i=\left(\frac{c_{i-1}+c_{i+1}}{2}-c_i\right) \; ; \; h_j=\left(\frac{c_{j-1}+c_{j+1}}{2}-c_j\right).$$

Associating the expressions (3) and (13) we obtain the network weight matrix elements, as

$$w_{ij} = \frac{1}{2}\sum_{k=1}^{N} h_i h_j g_{k-i} g_{k-j} \tag{14}$$

and the external input vector given by

$$I_i = -\frac{1}{2}\sum_{k=1}^{N}\left(y_k - \sum_{j=1}^{N} c_j g_{k-j} \right) h_i g_{k-i} \,. \tag{15}$$

The expressions (14) and (15) describe a recurrent neural network to determine each interface depth. A post processing calculates the thickness of each layer.

The physical property magnitude estimative

For it layer as defined above we consider constant the physical property. From the first estimative of ideal log (p_i^{est}), the actual physical property distribution (p_i^{rec}) is showed by the following expression

$$p_i^{rec} = (1 + p'_i)\, p_i^{est} \tag{16}$$

and p'_i is given by

$$p'_i = \frac{1}{2}\left(\sum_{j=1}^{M} \frac{1}{2^{j-1}} x_{ij} \right) \tag{17}$$

where x_{ij} represents the neuron outputs in the set {0, 1}.

Substituting the expression (16) in the expression (6), ignoring the terms not depending of x_{ij} and considering the punctual minimization, the p_i^{rec} value releases the sum in k and we obtain the following expression for the cost function

$$E = -\frac{1}{2}\left[\sum_{i=1}^{N} g_{k-i} \sum_{j=1}^{N} \frac{1}{2^{j-1}} \left(y_k - \sum_{i=1}^{N} p_i^{est} g_{k-i} \right) p_i^{est} \right] x_{ij} + $$
$$+ \frac{1}{8} \sum_{i_1=1}^{N} \sum_{i_2=1}^{N} \sum_{j_1=1}^{M} \sum_{j_2=1}^{M} \frac{1}{2^{j_1-1}} \frac{1}{2^{j_2-1}} p_{i_1}^{est} p_{i_2}^{est} x_{i_1 j_1} x_{i_2 j_2} \,. \tag{18}$$

Associating the expression (18) with the expression (3), we have the synaptic weight matrix elements as

$$w_{i_1 i_2 j_1 j_2} = \frac{1}{8} g_{k-i1} g_{k-i2} \frac{1}{2^{j_1-1}} \frac{1}{2^{j_2-1}} p_{i_1}^{est} p_{i_2}^{est} \tag{19}$$

and the external input vector is given by

$$I_j = -\frac{1}{4}\sum_{k=1}^{N}\sum_{i=1}^{N} g_{k-i} \frac{1}{2^{j-1}} \left(y_k - \sum_{i=1}^{N} p_i^{est} g_{k-i} \right) p_i^{est} \,. \tag{20}$$

With these expressions, we finished the mapping of well log deconvolution problem in the recurrent neural network environment.

Results

Now, we present an application with actual well log data from one borehole drilled in Namorado oil field, Campos basin, Brazil.

In Figure 3-A, we show the natural gamma ray log (black) and the processed log by neural network (blue). We observe the difference between the property value measured by the tool and the recovered value. For some log intervals we obtain GR values larger than the measured one; the inverse is also detected for other intervals, but in all logged depth interval the processed log shows a better vertical resolution than original GR log. This happens due the smoothing in the vertical tool response approximation, done by recurrent neural network. The core showed in Figure 3-B confirms the obtained results.

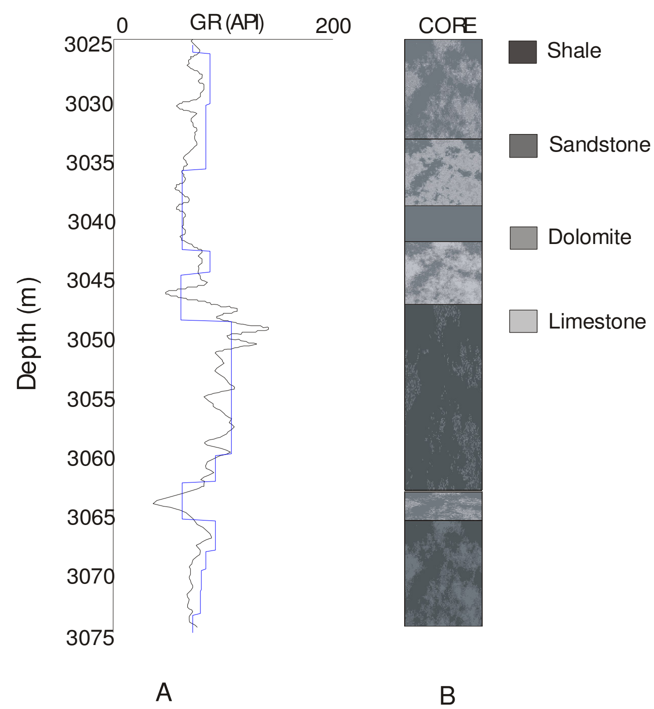

Figure 3. A - The natural gamma ray log (GR) (black) and the processed log (blue). B – Core

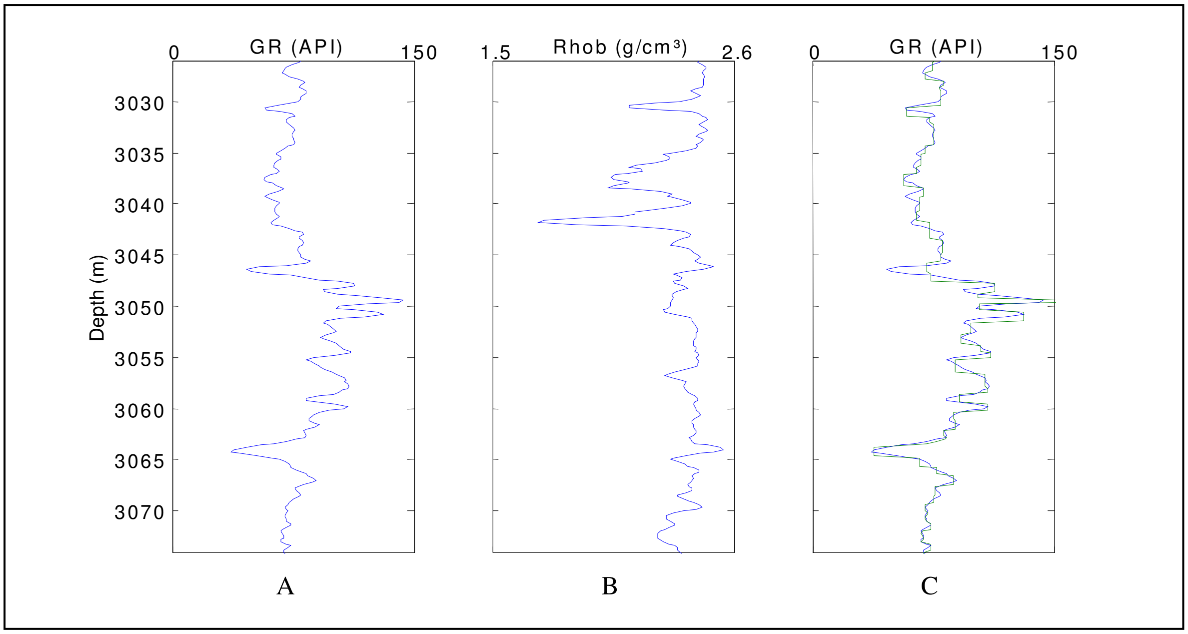

Figure 4. A – The natural gamma ray log (GR). B – The density log. C – The GR log (blue) and the processed log (green).

As the GR log exhibits a behavior suggesting a complex depositional setting, we show in Figure 4 the processing GR log with the density log (Rhob) used as the first guess about the ideal log. Figure 4-A shows the actual GR log and Figure 4-B shows the density log. In Figure 4-C, we can observe the differences between the physical property measured by the tool and the recovered values.

With this improvement in the data quality, we can obtain more realists rock property values in subsurface, improving the reservoir evaluation.

Conclusions

We presented a new look in the well log deconvolution problem introducing a particular recurrent neural network, which has intrinsic characteristics that improve the solution and reduce the computational time processing. Nowadays, this problem has been great attention of South America oil industry for the reevaluation of well logs in old oil fields.

Its application for actual well log data, showed efficiency for the lithologic logs, as natural gamma ray log, but its application is not restrict for this kind of well log, once none premise was done about the physical property to be processed. It means that this methodology is able to be applied for any kind of conventional well log. Particularly for natural gamma ray log, this method shows improvement in data quality and produced good values for shale volume, the principal utilization of the gamma ray log in formation evaluation.

This method opens the possibility of an autonomous information obtained from well log data and the search for the best subsurface representation at a low cost and computational effort.

Acknowledgements

The authors would like to acknowledge the support extended by UFPa/ANP/Prh-06 and CNPq for this work.

References

Andrade, A. and Luthi, S.M., 1993. Deconvolution of wireline logs using point-spread function. III Congresso Internacional da Sociedade Brasileira de Geofísica, Rio de Janeiro, Brasil.

Andrade, A., Luthi, S.M. and Guerra, C.E., 1995. Determinação de Interfacies em Perfis através de Rede Neural de Hopfield. V Congresso Internacional da Sociedade Brasileira de Geofísica, São Paulo, Brasil.

Baldwin, J.L., Otte D.N. and Bateman, R.M., 1989. Computer Emulation of Human Mental Processes: Application of Neural Network Simulators to Problems in Well Log Interpretation. SPE 64thAnnual Technical Conference, USA.

Barber, T.D., 1988. Induction Vertical Resolution Enhancement: Physics and Limitations. SPWLA 29th Annual Logging Symposium, June, San Antonio, paper O.

Ellis, D.V., 1987. Well Logging for Earth Scientists. Elsevier, USA.

Fischetti, A.I. and Andrade, A., 2002. Porosity images from well logs. Journal of Petroleum Science and Engineering, v.36, p.149-158.

Flexa, R.T., Fischetti, A.I. and Andrade, A., 2001. Determinação Estatística do Contato Óleo-Água em Perfis de Poço. VII Congresso Internacional da Sociedade Brasileira de Geofísica, Salvador, Brasil.

Hopfield, J.J., 1982. Neural networks and physical systems with emergent collective computational abilities. Proceedings of the National Academy of Sciences, USA, v. 79, pp. 2554-2558.

Nikravesh, M., 2004. Soft computing-based computational intelligent for reservoir characterization. Expert Systems with Applications, v. 26, pp.19-38.

Nosal, E.A., 1983. Statiscal determination of geophysical well log response function. Geophysics, v. 48, pp. 1525-1535.