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Novel methodology for accurate resolution of fluid signatures from multi-dimensional NMR well-logging measurements

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ABSTRACT

A novel methodology for accurate fluid characterization from multi-dimensional nuclear magnetic resonance (NMR) well-logging measurements is introduced. This methodology overcomes a fundamental challenge of poor resolution of features in multi-dimensional NMR distributions due to low signal-to-noise ratio (SNR) of well-logging measurements. Based on an unsupervised machine-learning concept of blind source separation, the methodology resolves fluid responses from simultaneous analysis of large quantities of well-logging data. The multi-dimensional NMR distributions from a well log are arranged in a database matrix that is expressed as the product of two non-negative matrices. The first matrix contains the unique fluid signatures, and the second matrix contains the relative contributions of the signatures for each measurement sample. No a priori information or subjective assumptions about the underlying features in the data are required. Furthermore, the dimensionality of the data is reduced by several orders of magnitude, which greatly simplifies the visualization and interpretation of the fluid signatures. Compared to traditional methods of NMR fluid characterization which only use the information content of a single measurement, the new methodology uses the orders-of-magnitude higher information content of the entire well log. Simulations show that the methodology can resolve accurate fluid responses in challenging SNR conditions. The application of the methodology to well-logging data from a heavy oil reservoir shows that individual fluid signatures of heavy oil, water associated with clays and water in interstitial pores can be accurately obtained.

1. Introduction

Nuclear magnetic resonance (NMR) well-logging is one of the most widely used technologies for characterization of the properties of the earth's subsurface. NMR tools can be lowered on an electrical cable in a well drilled into the earth, and a record of NMR measurements are made as a function of depth along the well as the tool is brought up. The depth of investigation of the NMR tools is few inches into the earth from the wall of the well [13]. A primary application of NMR well-logging is fluid characterization, which includes identification of the types of fluids present in the pores of the rocks and estimation of fluid volumes. Modern NMR logging tools can provide multi-dimensional measurements of diffusion (D), T_1 and T_2 relaxation time of pore fluids at Larmor frequencies ranging from few hundred kilohertz to several megahertz [8,7]. The contrasts in D, T_1 or T_2 responses can be used to differentiate the type of fluids and to estimate fluid volumes.

An example of a multi-dimensional NMR well log is simultaneous D-T_2 measurement. A pulse sequence commonly used for simultaneous D-T_2 measurement is the diffusion editing (DE) sequence [11]. DE sequences are similar to Carr-Purcell-Meiboom-Gill (CPMG) sequences except that the initial few echoes (usually one or two) are acquired with long echo spacings, and the subsequent echoes are acquired with the shortest possible echo spacing. The amplitude of the nth echo in a DE sequence consisting of a single echo acquired with long echo spacing is given as,

$$M(n) = \int f(g_0) \iint f(D,T_2) \exp\left(-\frac{TE_L + (n-1)TE_s}{T_2}\right) \times \exp\left(-\frac{\gamma^2 g_0^2 D(TE_L^3 + (n-1)TE_s^3)}{12}\right) dT_2 dD dg_0 \quad (1)$$

In Eq. (1) γ is the proton gyromagnetic ratio, D is fluid diffusion coefficient, T_2 is fluid relaxation time, TE_L and TE_S are the long and short echo spacing, and g_0 is background field gradient. $f(D,T_2)$ is the joint diffusion and relaxation time distribution, and $f(g_0)$ is the background magnetic field gradient distribution. The joint diffusion-relaxation time distributions, $f(D,T_2)$, are obtained from

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the inversion of the echo data acquired using DE sequences with variable long echo spacings. From either visual inspection of the peaks observed in the D-T_2 distributions (referred to as D-T_2 maps) or from simple interpolation techniques, the fluid types and volumes can be estimated. A fundamental challenge of these interpretation methods is that the features in the multi-dimensional maps are poorly resolved. The poor resolution obscures, or, in some cases, eliminates the contrasts in fluid responses thereby rendering fluid characterization impossible. There are two primary causes of the poor resolution of features in NMR maps – (1) poor signal-to-noise ratio (SNR) of NMR logging measurements and (2) the ill-conditioned nature of NMR inversions. Several factors could contribute to the poor SNR of NMR logging measurements such as high temperature of the subsurface earth, high salinity of drilling fluids, and small volumes of measurable fluids in rock pores. The inversion of NMR data is an ill-conditioned problem in the sense that many solutions could fit the data within the noise statistics [18]. The most common method for overcoming the ill-conditioned nature of NMR inversions is to use Tikonov regularization to find a solution that fits the data and satisfies additional constraints [20]. Regularization makes the solution stable but distorts the solutions by contributing to the broadening of the peaks. The following simulation illustrates the deterioration in the resolution of NMR maps due to regularization. The left panel of Fig. 1 shows a model D-T_2 response consisting of two peaks corresponding to two fluid types. The mean diffusion coefficients of the peaks were $2.5 \cdot 10^{-5}$ and $5 \cdot 10^{-6}$ cm^2/s which correspond respectively to the diffusion coefficients of water and a viscous oil at room temperature. NMR echoes were simulated using Eq. (1) for DE pulse sequence consisting of 8 echo trains with linearly increasing TE_L. A uniform gradient of 20 G/cm was assumed for the background magnetic field gradient. The short echo spacing (0.2 ms) and SNR (10) were representative of values for well-logging measurements. The pulse sequence parameters are shown in Table 1. The D-T_2 map obtained from inversion of the simulated data using Tikhonov regularization is shown in the right panel of Fig. 1. Compared to the model D-T_2 map, the inverted map shows a single peak. Such lack of resolution of peaks in multi-dimensional maps renders fluid characterization quite challenging.

This paper introduces a novel methodology for accurate resolution of fluid signatures from multi-dimensional maps obtained from NMR logging measurements. The methodology is based on an unsupervised machine-learning concept called blind source separation (BSS) that aims to uncover hidden patterns in the data without any a priori information or model. Broadly speaking, BSS is the separation of a set of signals from a set of mixed signals, without the help of information (or with very little information) about the source signals or the mixing process. BSS encompasses a family of techniques which utilize specific statistical and mathematical properties of the sources to enable separation. A powerful BSS technique is called non-negative matrix factorization (NMF). By imposing a non-negativity constraint on the sources, NMF produces a parts-based decomposition of the data [16]. Applications of NMF span a wide range including text mining, bioinformatics, spectral data analysis and clustering [17,9,15]. The application of NMF for fluid characterization from NMR logging measurements, first developed and introduced by Anand et al. [4], is outlined below.

The methodology for resolution of fluid signatures is based on the premise that the measured NMR response of a rock is a linear combination of NMR responses of different fluids present in the rock. This assumption is generally valid, and, in fact, inherent in the models used for inversion of NMR logging data. The normalized data (i.e., multi-dimensional maps) from the entire logged interval are vectorized and arranged as columns of a matrix. The resulting database matrix is factorized into the product of two non-negative matrices. The first matrix contains the unique NMR signatures of fluids present in the earth. The second matrix contains the relative contribution of the fluids in each measurement sample. The non-negativity constraint ensures that only additive, and not subtractive, combinations of the fluid signatures are allowed. The methodology is capable of uncovering the fluid signatures without any a priori knowledge. Another advantage of the methodology is that a large number of measurements are resolved into just a few (often fewer than 10) underlying features. The orders-of-magnitude reduction in the data dimensionality greatly simplifies the visualization of the fluid signatures and subsequent interpretation.

The paper is organized as follows. The next section describes the mathematical theory of the BSS-NMF (hereafter referred to as BSS) methodology. The following section shows the numerical validation of the BSS methodology for accurate fluid characterization from D-T_2 well-logging measurements. Simulations show that the BSS methodology can accurately predict the fluid signatures and volumes from low SNR D-T_2 measurements. The application of the methodology for extracting fluid signatures from T_1-T_2 measurements in a heavy oil reservoir is described in the last section.

2. Theory

Let us consider that there exists a collection of multi-dimensional measurements consisting of N samples. Each sample in the collection represents a measurement with distinct proportions of individual constituents of a system. Let v_j represent the jth sample in the collection. The number of elements in each multi-dimensional measurement is M. The BSS methodology postulates that each measurement in the collection can be approximated as a linear combination of unknown underlying features (called sources). Mathematically, the linear approximation can be described as follows:

$$v_j \approx h_{1,j}[w_1] + h_{2,j}[w_2] + \cdots h_{r,j}[w_r] = Wh_j \tag{2}$$

In Eq. (2), W is an $M \times r$ matrix containing the underlying features, w_i, as its columns. The array $h_j(r \times 1)$ contains the coefficients of linear combination. Combining all measurements in the collection, v_j, as columns of a matrix V $(M \times N)$ and combining the coefficients h_j as columns of matrix H $(r \times N)$, Eq. (2) can be written as,

$$V \approx WH \tag{3}$$

Matrices W and H are respectively called the feature and coefficient matrices. Eq. (3) shows that the linear approximation of Eq. (2) is equivalent to a matrix factorization. This factorization produces a linear decomposition of the data such that the data are expressed as the sum of its parts (i.e., sources). No assumption or a priori information about the underlying features is inherent in this factorization.

The factorization problem of Eq. (3) is solved by imposing a constraint that matrices W and H are non-negative. The non-negativity constraint ensures that the sources in matrix W are physically meaningful, and that only additive combinations of the sources are allowed. A cost function is defined that quantifies the reconstruction error between V and WH, as shown in Eq. (4):

$$\chi = \|V - WH\|^2 \tag{4}$$

The cost function is minimized with the non-negativity constraints on matrices W and H,

$$W \geqslant 0, \; H \geqslant 0 \tag{5}$$

The cost function of Eq. (4) is convex in W only or H only. However, it is not simultaneously convex in both W and H together. Therefore, a unique solution to the minimization problem is not always possible. Despite this limitation, numerical techniques are available that can provide a local minima of the cost function