Journal of Applied Geophysics 106 (2014) 37–49

Contents lists available at ScienceDirect

Journal of Applied Geophysics

journal homepage: www.elsevier.com/locate/jappgeo

Estimation of gas hydrate saturation in the Ulleung basin using seismic attributes and a neural network

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ARTICLE INFO

Article history:
Received 8 November 2013
Accepted 4 April 2014
Available online 18 April 2014

Keywords:
Gas hydrate
Neural network
Seismic attribute
Impedance inversion

ABSTRACT

Among the unconventional natural resources, gas hydrates have recently received much attention as a promising potential energy source. To develop gas hydrates, their distribution and saturation should be estimated, preferentially at the initial stage of development. In most cases, the distribution of gas hydrates can be identified by using seismic indicators including a bottom simulating reflector (BSR) and chimney/column structures, which indirectly determine the presence of gas hydrate. However, these indicators can be used only when they appear on a seismic image. Because the saturation of gas hydrate is generally calculated by using well logs, the information is limited to the well location. To overcome these limitations, seismic impedance inversion and neural network methods can be used. Seismic inversion enables the identification of a gas hydrate reservoir even if seismic indicators do not exist, and a neural network makes it possible to predict the gas hydrate saturation in a region of interest away from the wells by combining well logging data and other attributes extracted from the seismic data. In this study, to estimate the distribution and saturation of gas hydrates that are broadly distributed in the Ulleung basin of the East Sea, seismic inversions such as acoustic impedance (AI), shear impedance (SI), and elastic impedance (EI) were calculated, and then the seismic attributes (ratio of compressional wave velocity to shear wave velocity, Vp/Vs, and combinations of Lamé parameters, $\lambda\rho$ and $\mu\rho$) that have unique features in hydrated sediments were extracted. Gas-hydrate-bearing sediments displayed high AI, high SI, high EI (22.5°), low Vp/Vs ratio, high $\lambda\rho$, and high $\mu\rho$ compared the surrounding sediments. The sediments containing free gas displayed low AI, low SI, low EI (22.5°), high Vp/Vs ratio, low $\lambda\rho$, and low $\mu\rho$ due to the phase transition from gas hydrate to gas. By combining these findings, the distribution of gas hydrates was estimated even if seismic indicators were not present in the seismic profile. Using the extracted seismic attributes, as well as standard seismic attributes and three-phase Biot-type equation (TPBE)-derived saturation logs of gas hydrates at the wells which had a high correlation to the seismic attributes, the saturation of gas hydrates away from the wells could be estimated based on probabilistic neural network (PNN) predictions. To validate the predicted saturation, cross-validation of wells was undertaken. The average correlation coefficient between the predicted saturation and actual saturation logs at the UBGH-09 and UBGH2-10 wells was 82.6%. In addition, for the estimation of the saturation section of gas hydrate, a relatively high saturation region of gas hydrate corresponded well to the gas hydrate occurrence zone of each well.

1. Introduction

In recent years, high oil prices and advances in drilling technology have increased attention in developing unconventional energy resources. One such unconventional resource is gas hydrates, which have a shape resembling ice and are formed under certain high-pressure and low-temperature conditions in coastal sediments or permafrost (Coffin et al., 2007; Kvenvolden and Lorenson, 2001; Sloan, 1990). Marine seismic surveys and log measurements have confirmed that gas hydrates are widely distributed in the Ulleung basin of the East Sea, Korea (Kang et al., 2009; Kim et al., 2010; Seo et al., 2010; Shin et al., 2012; Yoo et al., 2008). In advance of gas production from these ice-like crystalline solids, the economics of any development including the initial investment cost and profitability should be considered. Exact estimations of gas hydrate distribution and saturation are crucial for the quantitative estimations needed to make a successful decision.

In most cases, the distribution of gas hydrates has been identified by using indirect seismic indicators of the presence of gas hydrates in the sub\surface. These include a bottom simulating reflector (BSR),

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http://dx.doi.org/10.1016/j.jappgeo.2014.04.006
0926-9851/

chimney/column structures, acoustic blanking, enhanced reflection, and gas seepage. In the Ulleung basin, the distribution of the gas hydrate stability zone (GHSZ) has been estimated using seismic indicators including BSRs, chimney/column structures, and acoustic blanking on a seismic profile (Kang et al., 2009; Yoo et al., 2008). However, if these seismic indicators are not present in the seismic section, they cannot be used to identify the distribution of gas hydrates. Alternatively, the calculation of gas hydrate saturation can be made from log measurements in a well. In the Ulleung basin, gas hydrate saturation has been calculated from the electrical resistivity and sonic logs at wells using numerical formulas proposed in previous publications (Kim et al., 2010; Seo et al., 2010; Shin et al., 2012). However, the calculation of gas hydrate saturation is only possible at the location of a well. Therefore, suitable techniques are required which can identify the distribution without seismic indicators and can estimate the saturation of gas hydrate throughout the seismic coverage beyond wells.

Seismic inversion can be used to identify a gas hydrate reservoir when seismic indicators are not present on the seismic section. In Ulleung basin, the frequency domain full-waveform inversion was implemented to extract the velocity information and identify the distribution of hydrate-bearing zone (Kim et al., 2013). A neural network makes it possible to predict petrophysical properties such as density, porosity, or saturation throughout the seismic coverage beyond the wells by combining seismic multi-attributes, which are physically relevant to log properties. In Ulleung basin, porosity, density, and P-wave logs were predicted in the seismic coverage beyond wells using a probabilistic neural network (PNN) (Lee, 2011) and multi-attribute transform technique (Riedel et al., 2013).

In this study, we extracted seismic attributes such as acoustic, shear, and elastic impedances (AI, SI, and EI), the ratio of compressional wave velocity to shear wave velocity (Vp/Vs), and combinations of Lamé parameters (λρ and μρ), and determined the distribution of gas hydrates in the Ulleung basin of the East Sea by using the seismic attributes generated. In addition, we estimated the saturation of gas hydrates over the seismic section based on PNN predictions using the seismic attributes obtained, standard seismic attributes, and gas hydrate saturations at wells calculated using a three-phase Biot-type equation (TPBE) (Lee and Waite, 2008).

2. Theory

2.1. Seismic inversion

Seismic inversion generally converts the reflectivity coefficients at geological interfaces into geologically meaningful layers (Swisi, 2009). Thus, it enables the lithological and stratigraphic identification of a reservoir and helps with the interpretation of petrophysical properties such as lithology and fluidity in a more geologically intuitive form (Savic et al., 2000). These features lessen the risk of uncertainty in gas hydrate reservoir development (Pendrel, 2006). The parameter estimated from seismic inversion on the basis of the seismic data and well logs is usually expressed as impedance, which occurs as one of the following three types: AI (acoustic impedance; P-impedance), SI (shear impedance; S-impedance), and EI (elastic impedance). These impedances can be extracted from two types of seismic inversion: prestack simultaneous inversion and elastic impedance inversion. Prestack simultaneous inversion (Hampson et al., 2005) simultaneously inverts the three reflectivity variables into P-impedance, S-impedance, and density using angle-dependent seismic data before CMP stacking based on the assumption that there are linear relationships between the logarithms of P-impedance [$\ln(Z_p)$] and the logarithms of S-impedance [$\ln(Z_s)$] and between the logarithms of P-impedance [$\ln(Z_p)$] and logarithms of density [$\ln(\rho)$]. Elastic impedance inversion (Connolly, 1999) inverts elastic impedance (EI) which is a function of P- and S-wave velocities, density, and an incident angle. Thus, EI can be used for inverting non-zero offset seismic data and is also useful for analyzing the amplitude versus offset anomalies of a reservoir at certain ranges of angle incidence.

2.2. Three-phase Biot-type equation (TPBE)

Considering the concept that gas hydrates display relatively high P- and S-wave velocities (because naturally occurring gas hydrates tend to substitute the pore fluids in sediment), Lee and Waite (2008) proposed the TPBE model, which can quantify gas hydrates from velocities in unconsolidated sediments. TPBE is based on the assumption that naturally occurring gas hydrate partially supports the sediment frame and fundamentally assumes idealized arrangements in which sediment, hydrate, and pore fluid create homogeneous, interwoven frameworks that have unique bulk and shear moduli affecting the P- and S-wave velocities:

$$V_P = \sqrt{\sum_{i,j=1}^{3} RE\left(R_{ij}\right)/\rho_b}, \quad V_S = \sqrt{\sum_{i,j=1}^{3} RE\left(\mu_{ij}\right)/\rho_b}$$

where V_p and V_s are P- and S-wave velocities, respectively, $\rho_b = (1-\phi)\rho_s + (1-C_h)f\rho_w + C_h\phi\rho_h$, ϕ is a porosity, C_h is the pore space hydrate saturation, and each subscript (s, w, h) indicates sediment grain, water, and hydrate, respectively. R_{ij} and μ_{ij} define a stiffness matrix and shear matrix, respectively. Two key parameters in the TPBE model are α and ϵ. α is the consolidation parameter and represents the stiffening effect of sediment caused by consolidation such as compaction, which primarily occurs due to the reduction in porosity and rise in inter-granular contacts when gas hydrate replaces fluids in the pore space. Parameter ϵ determines the extent to which the gas hydrate effectively reduces the unconsolidated sediment. For example, if $\epsilon = 0$, hydrate is treated as a sediment grain by substituting fluids in the pore space and plays a role in supporting and reinforcing contacts among sediment grains. If $\epsilon = 1$, hydrate does not contact sediment grains and has a floating status in the pore space where it supports sediment grains. This means that hydrate formation influences the effectiveness of compaction among sediment grains at the smallest level.

2.3. Seismic attributes and probabilistic neural networks (PNNs)

Since introduced in the oil and gas industry in the early 1970s, seismic attributes have been widely used to determine oil or gas reservoirs in the subsurface environment. Seismic attributes are a form of linear or non-linear transformation of seismic traces (Russell, 2004) and different types of information can be extracted from the seismic data (Taner, 2001). Once seismic attributes relevant to reservoir properties are optimally combined, a greater understanding of the reservoir is possible and geological features in the reservoir can be better delineated. One of the techniques that optimally merge these seismic attributes, a PNN, is a statistical algorithm referred to as a kernelized version of linear discriminant analysis, which was introduced by Specht (1990). The technique can also be considered to be a mathematical interpolation scheme that uses the neural network architectures of four layers, i.e., the input layer, pattern layer, summation layer, and output layer (Hampson et al., 2001). Several advantages of this method include its 1) easy and real-time training, 2) ability to determine the proper value of sigma, and 3) the permissibility of faulty data (Specht, 1990). This technique enables us to predict the petrophysical properties of a reservoir of interest away from the wells over the seismic volume by building a nonlinear relationship between seismic attributes and well log properties. This relationship is then used to predict well log properties of interest over the seismic volume. To obtain the relationship, PNN uses Gaussian functions, which link training samples generated from well log properties and seismic attributes derived from seismic data. Because the width of the Gaussian functions is controlled by a sigma value which varies for