Saturating pore fluid Bayes Indicator for reservoir mapping

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Abstract

A seismic-based reservoir properties estimation is implemented and tested in this work. The main goal in this work is to map oil saturated sands based on a sand-shale oil field system. We consider petrophysical measurements as source of information to construct a conditional probability density function (PDF) for water saturated sand and a conditional PDF for oil saturated sand. Using these PDFs' and seismic attributes from a reservoir cell, we compute the probability for water saturation given the attributes and the probability for oil saturation given the attributes. From these probabilities and following a Bayesian criterion we create an indicator for saturating fluid to this cell and the associated Bayes error. We analyze each reservoir cell to create a map for oil saturated indicator, water saturated indicator and the associated uncertainty.

Several seismic attributes are analyzed in this work and using the maximum entropy measured from these PDFs' we decide the most informative attributes and attribute pair to reduce uncertainty.

In the current time, the methodology was successful tested in well log data. Our next step is to test the methodology with seismic attributes and apply the methodology in a real situation.

Introduction

The 4D seismic have a wide potential in the monitorating and administration of reservoirs, allowing to identify fluids contacts, no drained oil portions, injection fronts and permeability barriers. The appearance of preferential water paths creates no drained oil areas. The 4D seismic becomes an important tool to identify the reservoir areas that still contains oil and, consequently, to elaborate recovery strategies.

Studies for fluid-saturation have been written frequently in the literature. Based on the Biot-Gassman theory, we study the effect of fluid saturation on seismic properties (Han and Batzle, 2004). Relationships between saturation and uncertainty, as predicted from Sengupta and Mavko (1998) and Mukerji et al. (2001), and principally methods based on Bayes criterion to reduce uncertainty (Gonzalez et al., 2002) were also of great interest for our work. A similar work, but more developed, can be founded in Mukerji, Mavko and Takahashi (2002). Only for visualization we study an application using Bayesian estimation theory through a workflow for analysis and prediction (Bachrach et al., 2004).

Our goal is to map sand reservoirs filled out by oil, through the seismic attribute answers in different saturation conditions. We use well log data as source of information to build a conditional probability density function (PDF) for an oil filed out sand/shale reservoir situation and to build a PDF for a water filed out sand/shale reservoir situation. Starting from these PDFs' and the seismic attributes estimated from seismic data associated to a reservoir cell we determine the most probable situation for the associated cell: *i*- filed oil reservoir cell or *ii*- filed water reservoir cell. A Bayes criterion is applied to this decision. We follow the mathematical theory developed by Takahashi (2000) based in previous works, that involves methods to quantify the information through the probability theory and methods to estimate based in the information, were used thoroughly.

Theoretical background

To express quantitatively the "state of knowledge" of rocks properties; probability density functions (PDFs') about these parameters, given a set of well log data representing *in situ* petrophysical measurement are computed. The "state of knowledge" (Takahashi, 2000), expressed by PDFs', can describe how well we know the targets and how uncertain our targets are. In estimation problems, the PDFs', supply a complete and quantitative description of the "state of knowledge " of each observed parameter, becoming a valuable information source.

However, as it is waited of the own statistics, the measures don't have a perfect state of knowledge - in other words, uncertainty zero. And it doesn't change in geophysical measures. This limitation can have cause in data acquisition, in the present noises, in the complexity of the nature, and in many other difficulties. Therefore, all and any form of minimizing the values uncertainty of properties in subsurface are been worth. In this point of view, it is noticed easily that a unique value they are not sufficient for estimates and that's the reason because the use of PDFs became viable in this work.

Initially, we worked with one-dimension PDFs', computing PDFs' for water saturation and oil saturation situations for each one of a series of petrophysical properties. We consider seismic velocities, Impedances, density, and others. To increase the amount of information we starts to work with pair of petrophysical properties, building two-dimensional PDFs' for oil saturation and water saturation situations. This work with a pair of properties was accomplished by the greatest reliability offered when we working with a pair.

Bayes decision criterion

With a PDF we can perform a reliable way to accomplish predictions using what was already produced. As it can be observed previously, in the use of the PDF, we can accomplish not only the forecast of the pore fluid, but we also can supply a trust in the forecast through an error.

Figure 1 shows a one-dimension PDFs' for oil saturated situation (red) and for water saturation situation (blue) given the density (ρ) information. The horizontal axis represents the density and the vertical axis represents the probability. The area below each curve represents the probability of each fluid in the observed point. These PDFs' were built from Well A log information. In this work there are two possible situations, water or oil saturation. We do not consider a two-phase situation.

The probability for water (oil) saturation given ρ is represented by Equations 1 (2).

$$\mathrm{p(water|}\rho\mathrm{)} = \frac{\mathrm{p(}\rho\mathrm{, water)}}{\mathrm{p(}\rho\mathrm{, water)+p(}\rho\mathrm{, oil)}} \qquad (1)$$

$$\mathrm{p(oil|}\rho\mathrm{)} = \frac{\mathrm{p(}\rho\mathrm{, oil)}}{\mathrm{p(}\rho\mathrm{, water)+p(}\rho\mathrm{, oil)}} \qquad (2)$$

Generalizing, we esteem the fluid observing the point crossed by the two curves, where ρ=2.19. In this point, the probabilities for oil and water saturated are the same. Hence, analyzing another point with ρ smaller than the point of equality (ρ<2.19), the fluid to be predicted is the fluid of the red curve (oil) and if ρ>2.19, we predicted the fluid of the blue curve (water). This method is denominated Bayes decision criterion. This criterion also accomplishes a selection of the petrophysical property that provide PDFs that possess smaller prediction error.

In spite of have a good decision criterion, we should analyze the error of each predicted point. Through the own Bayes decision criterion (equations 3 and 4), we considered an error for each point. Considering the dashed gray line in the Figure 2, the estimated Bayes error for an oil prediction associated to this point (ρ=2.15) is the probability given by the blue line (0,145 – red dot). Took as illustration, the point where ρ=2.19 in Figure 2 is the greatest possible error in this example (black dot).

$$\begin{aligned}&\mathrm{p(error\,|\,}\rho\mathrm{)} = \mathrm{p(water\,|\,}\rho\mathrm{)},\\ &\text{if } \mathrm{p(oil\,|\,}\rho\mathrm{)} > \mathrm{p(water\,|\,}\rho\mathrm{)}\end{aligned} \qquad (3)$$

$$\begin{aligned}&\mathrm{p(error\,|\,}\rho\mathrm{)} = \mathrm{p(oil\,|\,}\rho\mathrm{)},\\ &\text{if } \mathrm{p(water\,|\,}\rho\mathrm{)} > \mathrm{p(oil\,|\,}\rho\mathrm{)}\end{aligned} \qquad (4)$$

In that way we noticed that the error of each prediction could be different, even with the same probability. This, because the error will be dependent of the other fluid PDF.

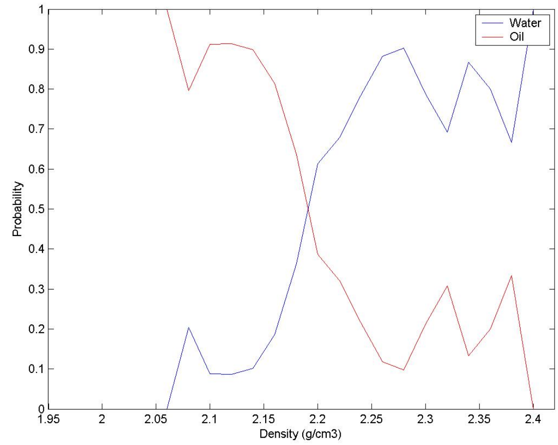

Figure 1: $\mathrm{p(water\,|\,}\rho\mathrm{)}$ (blue line) and $\mathrm{p(oil\,|\,}\rho\mathrm{)}$ (red line)

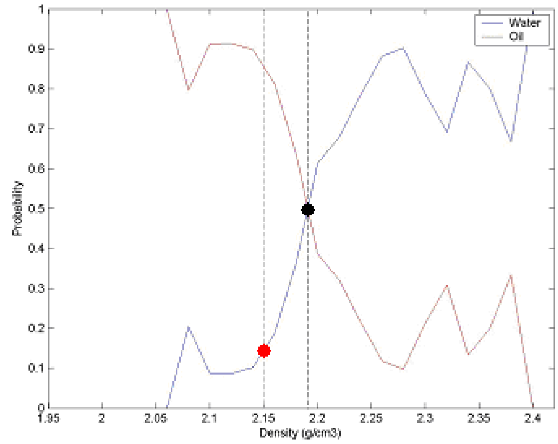

Figure 2: The associated Bayes error in ρ=2.15 (red dot) and the greatest possible error (black dot)

Method

Starting from a set of Well A log data, where we have known a water saturation condition estimated with good resolution, synthetic data were generate for new saturation conditions, through the Fluids Substitution (Biot-Gassmann theory) (Han and Batzle, 2004). Figure 3 shows elastic velocities (V_P, V_S) and density logs for the original saturation (water) and for oil saturation after fluid substitution.

After having accomplished the fluids substitution, we compute for each saturation condition others petrophysical parameters of interest – P and S wave impedance, Poisson's ratio, shear modulus and Young modulus – through the equations 5, 6, 7, 8 and 9.

$$\sigma = \left[\frac{\left(0.5\left(\mathrm{V_p V_S}\right)^2 - 1\right)}{\left(\left(\mathrm{V_p V_S}\right)^2 - 1\right)} \right] \quad (5)$$

$$\lambda * \rho = \left[\left(\mathrm{V_p}^2 \rho^2\right) - 2\left(\mathrm{V_s}^2 \rho^2\right) \right] \quad (6)$$

$$\mu * \rho = \left(\mathrm{V_s}^2 \rho^2\right) \quad (7)$$

$$I_p = \left(\mathrm{V_p} \rho\right) \quad (8)$$

$$I_s = \left(\mathrm{V_s} \rho\right) \quad (9)$$

where:

σ = Poisson's ratio

λ = Young modulus;

μ = Shear modulus;

ρ = Density;

I_p = P wave impedance;

I_s = S wave impedance.

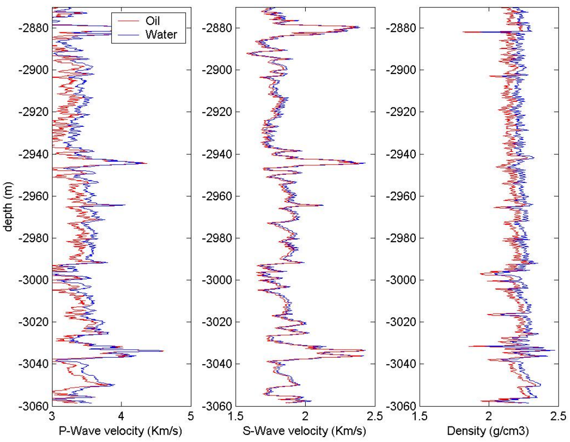

Figure 3: The elastic velocities (V_P, V_S) and density logs for the original saturation (water) and for oil saturation after fluid substitution

With this set of petrophysical parameters, we compute a set of conditional PDFs for oil and water saturation, given the associated property. The errors associated to each parameter were computed, allowing an analysis to evaluate the most informative petrophysical property.

Starting by the development of Takahashi (2000) we noticed that the combination of two parameters would supply more information about the fluid. Conditional two-dimensional PDFs were computed for pair of petrophysical parameters. As previous, we compute the associated error for each pair, observing the amount of information that each pair of petrophysical parameters supplied.

The conditionals PDFs generated are presented in the Figure 4 (one-dimensional) and Figure 5 (two-dimensional). Tables 1 and 2, show the Bayes errors computed from the PDFs'.

Well log tests

To test the methodology we consider another well (Well B) with a set of log from the same reservoir from Well A. The petrophysical properties from Well B are plotted on the PDFs' previously computed (showed on figures 4 and 5).

Figures 6 and 7 present the PDFs' with some of the samples of Well B. The tables 3 and 4 show the Bayes Indicator, the associated Bayes error and the saturation log from Well B to compare.

Results and conclusions

The fluid indicator computed using this methodology, together with the computed error and the accomplished tests, brought us to the following conclusions:

1) Investigation using the attributes clearly revealed that the uncertainty about rock properties cannot be reduced by data manipulations. Instead, data acquisition, physics, and geological knowledge bring information about rock properties.

2) The type of saturating fluid influences the P wave velocities, if only because of the compressibility of the fluid. For S wave, it may be assumed that the liquid has no effect on velocities and the little effect observed is exclusively a density effect. The influence on the P and S impedances can be explained in the same way.

3) As well as the S wave is not influenced by the saturation fluid change, the shear modulus also doesn't vary with this change. The attributes coming from those parameters are not sensible regarding fluid. Through the Bayes error acquired we detached the V_P / V_S, $\lambda * \rho$, and σ as the best parameters for the analysis.

4) Among the pairs of attributes we stand out the following pairs: *i*- V_P and σ; *ii*- $(\lambda - \mu) * \rho$ and $\mu * \rho$; and *iii*- V_P / V_S and I_P. These pair of petrophysical properties stands out as visually as for the calculated Bayes error.

5) Some of parameters show low information, but when combined with other, they can supply relatively more information. From this precept, we affirm that the work with pairs of petrophysical properties is more reliable than the work with alone parameters.

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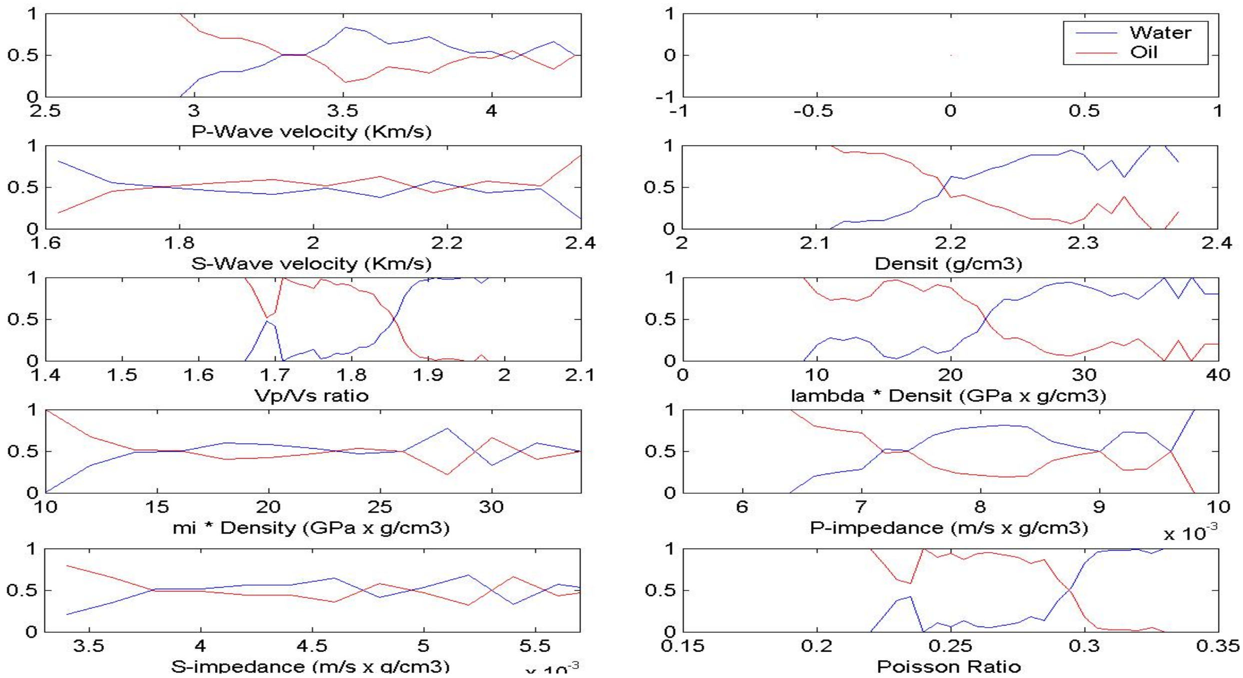

Figure 4: One-dimension PDFs' computed to each petrophysical property

Petrophysical property	V_P	V_S	ρ	V_P / V_S	$\lambda*\rho$	$\mu*\rho$	I_P	I_S	σ
Bayes error	0.3321	0.4503	0.2482	0.1222	0.1759	0.4517	0.2960	0.4562	0.1257

Table 1: Bayes errors computed to each graphic showed in Figure 4

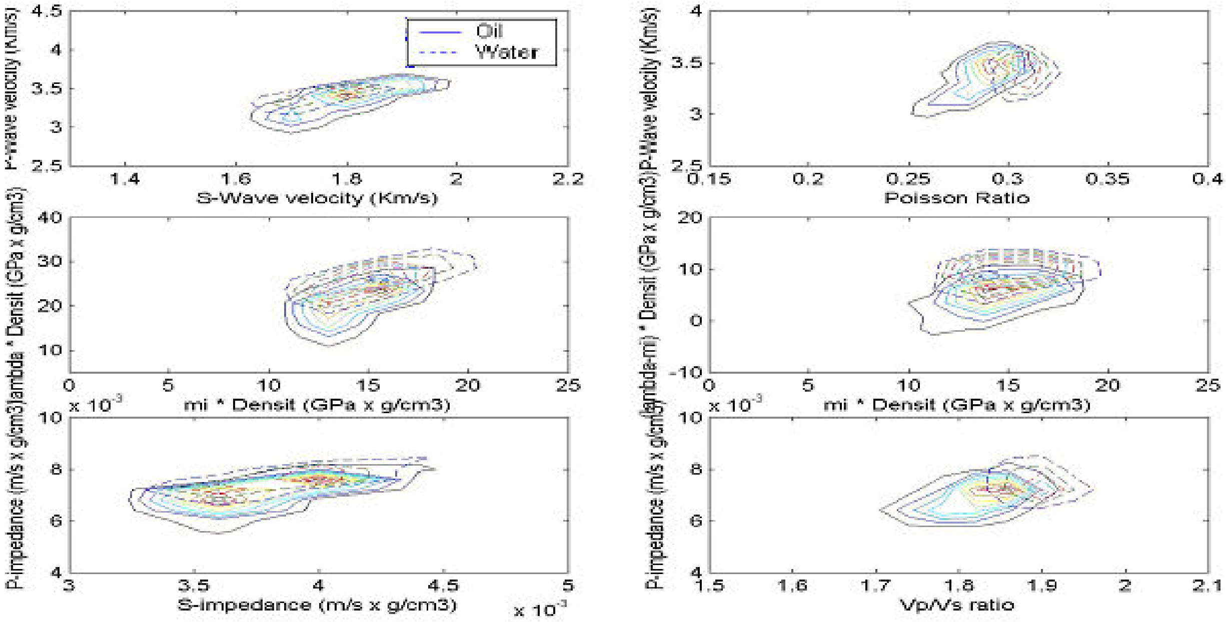

Figure 5: Two dimension PDFs' to each pair of petrophysical properties

Pair of properties	$V_P - V_S$	$V_P - \sigma$	$\lambda^*\rho - \mu^*\rho$	$(\lambda-\mu)^*\rho - \mu^*\rho$	$I_P - I_S$	$I_P - V_P\text{-}V_S$ ratio
Bayes error	0.2545	0.1005	0.1196	0.1113	0.2927	0.1270

Table 2: Bayes errors computed to each graphic showed in Figure 5

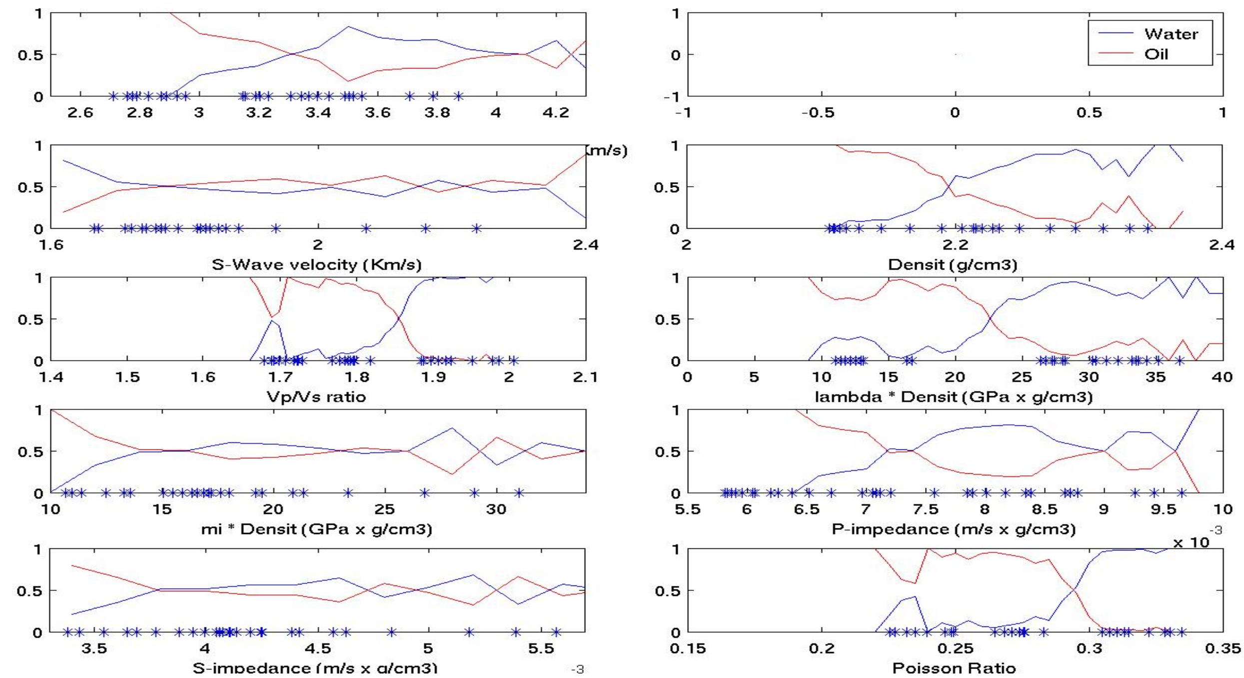

Figure 6: One dimension PDFs' with some of the samples of Well B

	V_P / V_S (1,797)	V_P / V_S (1,888)	V_P / V_S (1,978)	λ*ρ (12,07)	λ*ρ (16,35)	λ*ρ (30,29)	σ (0,245)	σ (0,283)	σ (0,328)
Bayes Indicator	“oil”	“water”	“water”	“oil”	“oil”	“water”	“oil”	“oil”	“water”
Bayes error	0,090	0,057	0,013	0,252	0,050	0,117	0,103	0,152	0,019
Well log saturation	oil	water	water	oil	oil	water	oil	oil	water

Table 3: Bayes Indicator, Bayes errors and well log saturation fluid for some samples showed in Figure 6

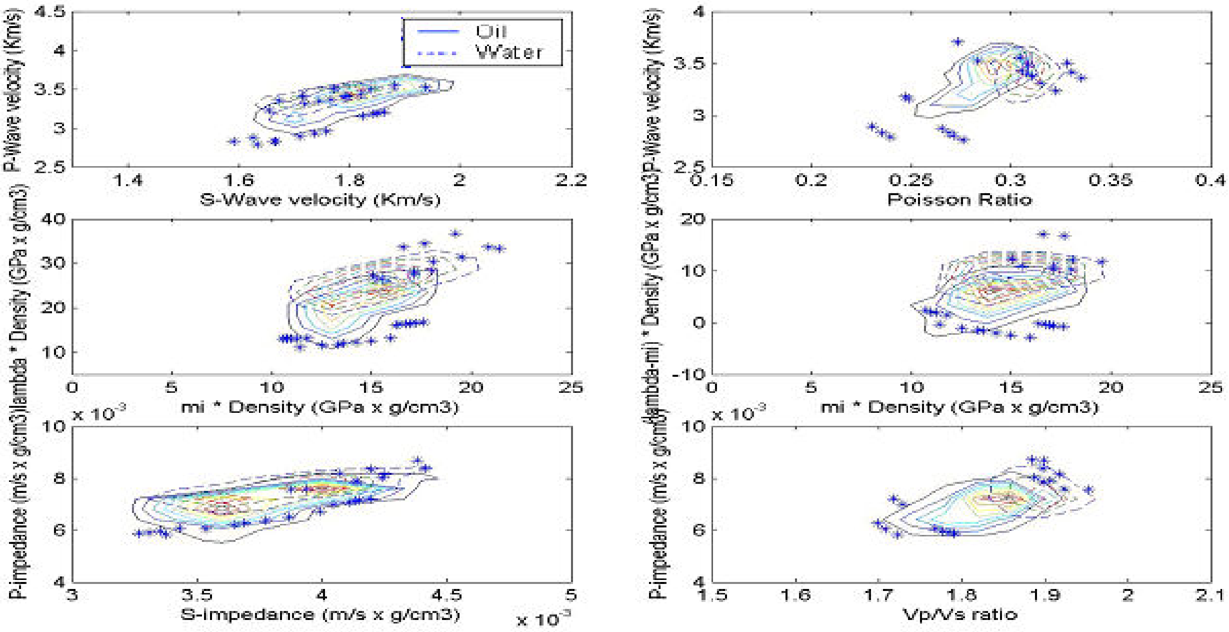

Figure 7: PDFs to each pair of attributes and the tested points

	V_P (3.399) – σ(0.308)	V_P (3.548) – σ(0.304)	V_P (3.154) – σ(0.249)	(λ-μ)* ρ(10.88) – μ*ρ(15.52)	(λ-μ)* ρ(12.22) – μ*ρ(18.08)	(λ-μ)* ρ(1.806) – μ*ρ(11.24)	I_P(0.0079) – V_P / V_S (1.898)	I_P(0.0063) – V_P / V_S (1.699)	I_P(0.0059) – V_P / V_S (1.797)
Bayes Indicator	“water”	“water”	“oil”	“water”	“water”	“oil”	“water”	“oil”	“oil”
Bayes error	0,145	0,091	0,075	0,098	0,053	0,021	0,0165	0,075	0,018
Well log saturation	water	water	oil	water	water	“oil”	“water”	oil	“oil”

Table 4: Bayes Indicator, Bayes errors and well log saturation fluid for some samples showed in Figure 7