Characterizing Geological Facies using Seismic Waveform Classification in Sarawak Basin

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Abstract. Numerous effort have been made to build relationship between geology and geophysics using different techniques throughout the years. The integration of these two most important data in oil and gas industry can be used to reduce uncertainty in exploration and production especially for reservoir productivity enhancement and stratigraphic identification. This paper is focusing on seismic waveform classification to different classes using neural network and to link them according to the geological facies which are established using the knowledge on lithology and log motif of well data. Seismic inversion is used as the input for the neural network to act as the direct lithology indicator reducing dependency on well calibration. The interpretation of seismic facies classification map provides a better understanding towards the lithology distribution, depositional environment and help to identify significant reservoir rock.

1. Introduction
Reservoir characterization is a very risky task and multiple methods and techniques have been developed to reduce the uncertainty during the stage of exploration and production. There are few factors that contribute to the uncertainty including the limitation of seismic resolving power, insufficient well logs, the approximation of physical model and natural variability in rock [9][5]. Hence, a method using statistical approach such as automated facies recognition of neural network had been performed to reduce the uncertainty. It is also known as artificial intelligence and automatic clustering and has become popular on 90s due to its successful application in other field of study such as biology and economy.

Hence, more study were conducted to see the ability of artificial neural network to recognize the populations of similar multi-attribute response [16] and to select the right attributes from the list of multi-attribute in the input process [19]. The use of multi-attributes in the seismic facies recognition is very important as it enables the interpreter to analyse different aspects of seismic response (energy, frequency, phase, geometry and texture, etc) simultaneously, generating a map of facies or correlating seismic response to engineering/production data [15][12][1][2][4][6]. The other important use of neural network in reservoir characterization is to classify the seismic facies and pattern recognition in which various algorithms have been developed, proposed and applied to improve the network [3][18]. Since seismic data contain huge amounts of data samples and they are highly continuous, greatly redundant and significantly noisy [8], neural network especially self-organizing maps (SOM) able to...
delineate the structure of the data and to reduce the dimensionality. Seismic facies classification algorithms attempt to mimic human pattern recognition and can be applied to a more arbitrary collection and greater number of attributes [19]. Neural network also has been used to extract structural lineaments [10], lithological classification [17] and replacing and to improve seismic inversion techniques [14][13]. The approach has been proven to have a better result than any other technique especially when it is used in highly heterogeneous formation [7].

Neural network is the best automatic and supervised method used to identify and to classify the seismic facies to multiple classes due to its ability to suppress the noise, handle the complex and large database and to eliminate the need of complex statistical technique. Hence, the objective of this paper is to characterize and to predict the lithofacies distribution of the study area by interpreting the seismic facies classes and relating them to geological facies. As now the stratigraphic trap is becoming widely popular, identification of lithofacies distribution helps to reduce the risk for the future exploration. The lithofacies distribution can be predicted by using seismic waveform classification of neural network which plays important role in reducing the subtleness of the changes of seismic amplitude and also phase. The seismic used for the classification is the P-impedance seismic as it acts as the direct lithofacies indicator with less dependency on the wells. The study is important to discover the ability of neural network to propagate the clustering in the seismic especially away from the wells. The interpreted lithofacies map can also help to reduce uncertainty in characterizing the reservoir by highlighting the prospect (gas sand) and non-prospect area (brine sand).

2. Geological Settings
K field is located in Borneo Basin of Malaysia. The main reservoir is F3 sand with the thickness about 23m and depositional environment ranging from holomarine inner to outer neritic or possible ponded turbidites. The coarsening upward trend of the sand probably characterized by the transition of environment from holomarine outer-middle-inner which formed during the highstand system tract [8]. Being the post carbonate siliciclastic and due to interaction between eustacy and progradation behaviour of the sand against the carbonate build-ups, it is believed the hydrocarbon migration of F3 to be originated from underlying carbonate itself as it is found to be underfilled. Due to stacking pattern of forced regression, the vertical migration from carbonate to upper silt and sand is found possible proven by interpretation of multiple seismic section regionally.

3. Data Scope
Seismic dataset was acquired on 2004. The full-fold 3D area comprised an area of 1871.5 km^2 forming a rectangle 50 km in length by 37.8 km in breadth. The quality of 3D seismic data is good. Most of major markers above 2.5 seconds (Precarbonate) have good lateral continuity and clear discontinuity at fault locations. Structural and stratigraphic features can be clearly seen from the 3D data. The dominant frequency at major reservoir zone from full stacking volume is around 35Hz to 40Hz, but the seismic wavelet shows mixed phase characteristic. Three wells are provided in the field; K-1, K-2 and K-3. All wells are used for the seismic-to-well correlation. Basic wireline logs such as gamma ray, neutron, density, resistivity, S-slowness, P-slowness and saturation are provided for further use. However, in K field, the porosity log are not used as the reading shows inconsistency with the lithological data. The type of rock mineral might contribute to this issue, but no further research is made.

4. Research Method
There are two types of seismic waveform classification in the study; voxel based and trace based. The time interval used for waveform analyses is different according to the method. Voxel based consists of three data axis; inline, crosslines and time/depth meanwhile trace based consists of only inline and xline. Voxel based method performed the waveform classification in voxel or 3D seismic pixel manner which is more details compare to the trace based method. Trace based takes certain interval of seismic volume and utilize the average shape or morphology of seismic waveform for classification.
purpose. Both methods can utilize multiple attributes volumes as the main input for classification. However, in voxel based, the final output will consist of seismic facies volume whereas a map in trace based method. Principal component analysis (PCA) is conducted to reduce the redundant data and noise in multi-attributes volume or even a single seismic volume before being used as input for seismic waveform classification. In this study, same neural network principle is used for the classification in both of the methods with the same type of input which is P-impedance. However, in voxel based, the wells are calibrated and each of the classification class is being defined based on the lithofacies response in the wells. The well calibration in trace based method is not possible due to clustering of the wells in which the reservoir interval remains consistent with only slight variety in terms of lithology, porosity and thickness in all three wells. Hence, it is difficult to represent the changes of reservoir behaviour laterally and its effect to the seismic waveform morphology. However, the differences can be noticed vertically as the shale transitioning to sand with various thickness and porosity and these differences can only be captured by using the voxel based method.

![Figure 1: The interpreted reservoir horizon of F3 with the thickness of about 23m. Below is F3A which appears to be thinner than F3](image)

Most of the seismic waveform classification study use the reflectivity seismic data as the main input beside other multi attribute such as amplitude. But due to the lack of well representation for seismic waveform, the focus is now shifted in using only seismic as the direct rock or lithology indicator by reducing the use of well calibration. The rock parameter identified to be the best in discriminating the lithology is the P-impedance. Hence, pre-stack inversion or also known as simultaneous inversion is conducted and being used as the input for seismic waveform classification.

5. Application and Results

5.1. Trace based
The time interval of -4ms+19ms is used with the P-impedance seismic cube as the input data. The training of neural network is conducted using 100 iterations and seven class number. Each of the class if represented by the trace model which is also known as the cluster centre or the best representation of the class. The distance curve shows constant sloping line which indicate the cumulative difference between the neighbour classes are equal. If too much class used, the slope will be in straight line meaning no much differences between the classes but if the number of class is too small, the slope will be drastically steep indicating the differences is too big and very geologically unlikely. The seismic waveform classification shows the final result map (Figure 2).

Based on the inversion result, the lowest P-impedance is shown by the gas sand follow by shale and sand with the highest quality or coarsest grain which is represented by the highest impedance. As seismic inversion can be used as the direct rock indicator, the class 1 or the lowest impedance based on the seismic morphology, can be defined as the gas sand, followed by class 2 and class 3 which possibly correlated with the shale lithology. The sudden sharp notch at the distance curve in class 4 might indicate the changes of lithology from shale to sand. As the P-impedance trace model is becoming higher in impedance, the lithology as well changes to coarser, cleaner type of sandstone. This coarser and cleaner type of sandstone can also be known as good brine sand and if the poor quality sandstone, lower in impedance is known as poor brine sand. Multiple seismic attributes such as
RMS amplitude, sweetness and RMS frequency are also generated to provide more evidence for the gas sand (Figure 4).

![Figure 2: a) The seismic facies classification map produced from trace based method. Each of the colour corresponds to different classes b) The above is the trace model and its corresponding colour code. The class is labelled first from left to seventh to the most right. Distant curve below shows cumulative difference between the neighbour classes.](image1)

![Figure 3: a) The sweetness attribute b) RMS frequency attributes](image2)

5.1.1. Principal Component Analysis (PCA). Principal component analysis (PCA) is used to reduce the noise and the redundant data. It finds the best representation of data in multiple dimension according to the input data. It is an unsupervised, represented by two principal components called eigenvector/eigenvalue in which the first component denoted the direction of maximum data distribution or variances meanwhile the second component is smaller than the first and perpendicular to it. Since in this study, pre-stack inversion is used, PCA is utilized to determine the best cloud or cluster data and any data outside this cloud is best to be removed as it does not contribute much to distribution of data. These outside data can also be called noise. PCA can only be used in trace based method as the input data is count as traces and not treated as the volume as in the voxel based method. In voxel method, one seismic volume is enough for one main data principal representation. Five components are used as the input for the trace method (Figure 4). Any data with low contribution to the cloud data with eigen values are usually less than one, are eliminated from being analysed in neural network. These outside data might be noise and if included, can give a lot of effect during the classification process.
Figure 4: Principal component analysis of P-impedance cube. The components consist of seismic traces and eigen values indicate the contribution of the components to data cloud.

5.2. Voxel Based

Voxel-based method is a microslicing method in which the seismic is being sliced into smaller interval based on the minimum/maximum, inflection points, zero sine or zero crossing. The seismic waveform classification is then conducted in smaller interval, hence the provided result is more detail in capturing the lithology changes vertically and laterally. As waveform classification in traces method only deal with inline and xline information, voxel based method is in 3D with the time as third axis or domain. The inflection points are used for the microslicing and -49ms+77ms of F3 horizon as the input for the neural network. Seven number of classes is selected with no PCA analyses. The results are shown below.

Figure 5: The voxel based in a) K1 b) K2 c) The trace model class from the voxel based
The coarsening upward trend of gamma ray is marked by the transition of colour from red to yellow indicating the increase of impedance across the first class to the seventh class (Figure 5). The red colour class or the first class can be correlated to the gas sand in the well indicating the lowest impedance class. The red coloured class can also be seen in the upper interval of F3 signify these sands are also a gas sand. Some of the F3 gas sand is also being classified as light and dark green colour or the second and third trace class respectively indicating the increasing in impedance as the facies change. Below the gas sand, is the poorer quality of sand compared to gas sand, but still classified as colour yellow or good brine sand due to its high impedance.

In order to observe the lateral changes of these lithology class, time slice is generated by +4ms in difference (Figure 6). A1 shows the gas sand distribution which is started to be seen at 4ms below the F3 horizon and becoming less obvious as it reaches the bottom of the reservoir. A2 and A3 is mainly yellow colour coded class, corresponds to good brine sand can be seen as early as +2ms and become bigger throughout the reservoir. A4 sand comes later indicating the above part of A4 is mostly shale and silty and just like A2 and A3, the area increases towards the bottom of reservoir. A5 is green colour coded class and the lithology is consistent along the interval. By observing the time of the lithology formation and the classification of these lithology, it is then possible to understand the lithology distribution in the study area. A2 sand for example has better quality sand compare to A4 since A4 sand come later at 4ms below the F3 horizon meanwhile A2 already formed at 2ms. A4 is interpret to be a better brine sand and A2 is poor brine sand. Based on time of the lithology formation, A3 is also observed to be formed at the same time as A2. They are possibly in the same quality of brine sand. Since A5 is classified as in green coded class, it is inferred as shale lithology. A6 can also be inferred as shale due to characterization of this class by red and green colour code.

Figure 6 : The horizon slices for every +4ms and +2ms of voxel based classification volume. Each of the lithology area are marked with code A1, A2, A3, A4, A5 and A6

6. Discussion
The response of trace model in trace based method can be verified with additional information from the voxel based method. The development of the lithofacies along the reservoir interval can be observed using the voxel based method which use the well calibration to increase the accuracy of lithology interpretation. The transitioning of class from first class (red) to seventh (yellow) class indicate the coarsening upward sequence of gamma ray when being calibrated to the well information indicating the increase in the value of P-impedance. The integration of well and seismic shows that the
highest quality of sand (based on the gamma ray value) is marked by the highest value of P-impedance and decreasing as it becomes shalier. The lowest P-impedance meanwhile marked by gas sand. Trace method however is very depending on the relationship of P-impedance to the lithology from the feasibility study and inversion data without integration of the lithofacies from well. However, by combining these two methods, the uncertainty in the trace based method is complemented by taking the advantage of using well in the voxel based method.

Using the trace based map, the seventh class is interpreted as good brine sand as P-impedance is high. This result is also agreeable with the result from the voxel method. Area A2 and A3 both shows the good brine sand. The brownish-orange colour class of fifth and sixth class are also conformable with the voxel result of A4 which is poor brine sand as the upper interval is mostly dominate by silt and shale. The shale area of A5 and A6 also shows the same responds of shale in the trace based method. Both of the methods are in conformable of each other which draw the conclusion on the final interpreted lithology map of K field (Figure 7).

7. Conclusion
The integration of wells and seismic increase the accuracy of the neural network classification result as each of the waveform class is well defined by different lithofacies, characterized by the gamma ray value of the well. However, with less dependency on the wells, the trace method is still proven to produce the best lithofacies classification as it appears conformable with the voxel based method which highly dependent on the well calibration. However by combining the result from voxel based and trace based, the final interpreted seismic facies map is highly convincing. It is now possible to delineate the area of brine sand and gas sand with the lithology various from poor to good.

Resolution of seismic is still the main issue in the study. The resolution of the seismic in the study area is around 10m. The reservoir under the resolution value cannot be detected which make it impossible to perform the waveform classification. The extent of transition zone in the interpreted map can be mapped if seismic able to resolve the thin layer or the real termination point of the reservoir. By knowing the zone, the final volumetric assessment can either be increased or decreased. However,
neural network already able to solve multiple issue on noise, redundancy of data and dimensionality problem especially when multi attributes are used.

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