



Delineation of channels using unsupervised segmentation of texture attributes

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Keywords

Channels, ANN, Texture Attributes

Summary

Seismic facies identification and analysis with regards to geological environment is one of the important tasks in geological and geophysical studies. Pattern identification through seismic attributes or seismic waveform classification provides insight into facies analysis. Information from different seismic attributes can be integrated using the data-driven unsupervised clustering algorithms. It's an effective tool for understanding patterns hidden in the seismic data by means of combining information from different seismic attributes. Being a data-driven approach, it doesn't require external information from well logs or other sources for clustering of seismic waveforms leading to delineation of geological features.

In this article, unsupervised segmentation of seismic waveforms is studied in comparison with traditional attributes and GLCM based texture attributes for delineation of a channel in the study area. A comparative analysis of texture attributes are also presented and discussed in terms of channel delineation. Unsupervised waveform segmentation was also performed to compare the response of waveform segmentation on seismic amplitude data and seismic attributes. To integrate information from different seismic attributes, an unsupervised neural network is also used for clustering similar seismic responses from channel. The study resulted in delineation of a meandering channel complex in the study area.

Introduction

The objective of unsupervised segmentation of seismic data is to extract natural clusters in a data set based on the character of the seismic waveforms. In addition to seismic amplitude data, seismic attributes provide required information for extraction of clusters from the seismic data for seismic facies analysis and helps in delineation of subtle stratigraphic features like channels

Various attributes based on amplitude, frequency, phase, dip and coherency provides qualitative information of the physical and geometrical properties of the subsurface. Identification of desired geological feature or properties of interest generally requires integration of various seismic attributes. Many methods based on the variations in seismic response to delineate geological features or facies analysis have been proposed by various authors (e.g., Jin et al., 2007; Li and Castagna, 2004; Saggaf et al., 2003).

Automated clustering or pattern-recognition techniques were also applied and discussed by various authors in the literature for delineation of geological features and facies analysis. Most of these techniques target similarity in wave

shapes, which may correspond to the same geological feature. Analysis of lithological changes in a reservoir from seismic data has been presented by Mathieu and Rice (1969). In addition to discriminant-factor analysis Dumay and Fourier (1988) used Principal Component Analysis for automated clustering from seismic data. Simaan's (1991) has proposed to segments the seismic section into zones of common signal characteristics using knowledge based system. Fournier and Derain (1995) have proposed combination of seismic facies analysis with seismic-attribute calibration for characterization of reservoir properties. Yang and Huang (1991) and West et al. (2002) proposed artificial neural networks for seismic facies analysis and classification.

Unsupervised pattern classification using Kohonen self-organizing map has also been proposed by Coléou et al. (2003), Taner et al. (2001), Zhang et al. (2001), and Matos et al. (2003a, b, 2004a, b., 2007) as a powerful method for facies analysis.

Although there are various methods for unsupervised classification which can be applied to the seismic data for facies analysis, several of them are reviewed by Barnes and Laughlin (2002), and found that the clustering algorithm are less important than the choice of used sets of seismic attributes. This set of seismic attributes, used for facies analysis, often depends on the objective of the study.

Meldahl et al. (1999) used neural network with seismic coherence and energy attributes to identify hydrocarbon chimneys. Similar methodology was adapted by West et al. (2002) for seismic facies analysis of a channel system.

Gao (2007) has proposed use of texture attributes for facies analysis in area from offshore Angola. Corradi et al. (2009) has also used texture attributes to map sand, sealing vs non-sealing shale facies in offshore West Africa.

In the present study we investigated the use of GLCM based texture attributes along with the conventional seismic attributes for delineation of channels using unsupervised learning algorithms. Texture attributes provides the information about adjacent amplitude values with respect to point of operation in various probabilistic measures namely, Energy, Entropy, Homogeneity etc.

In this paper, a comparative analysis has been done to study the efficiency of GLCM based texture attribute for unsupervised clustering for delineation of channel system.

Data and Methodology

The input for the present study is 3D pre stack time migrated (PSTM) seismic volume, from the Tarapur low of the Cambay basin. The objective of this study is to understand the effect of various seismic attributes on unsupervised clustering for delineation of channel system. Figure-1 shows the workflow designed for this study. Data conditioning using, Dip Steered Median Filter (Santosh et al. (2013) was applied on the input data for removal of noise which may harm the unsupervised clustering of the data.

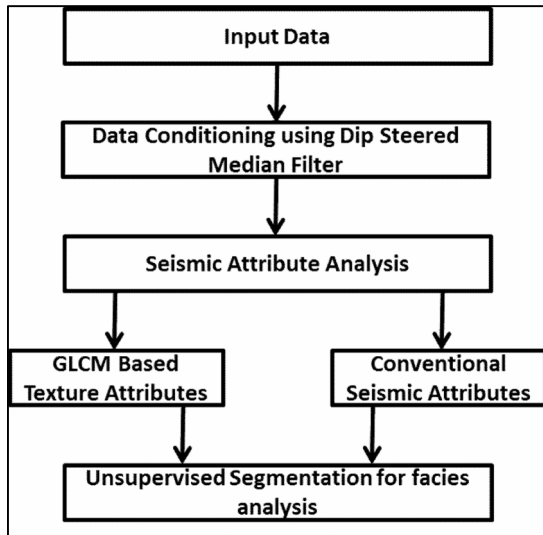


Figure 1 Workflow adapted in the study

Seismic Attribute Analysis

A Channel like feature is observed on the time slice near 950 ms corresponding to the Miocene age in the area. Figure-2 shows the conditioned seismic data using dip steered median filer (DSMF) on the time slice and RMS amplitude attribute on time slice 950 ms, showing channel like feature.

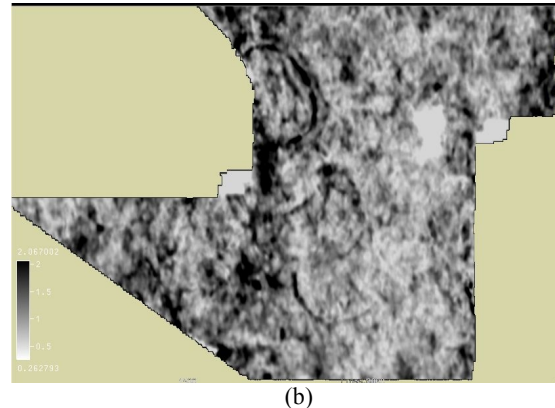
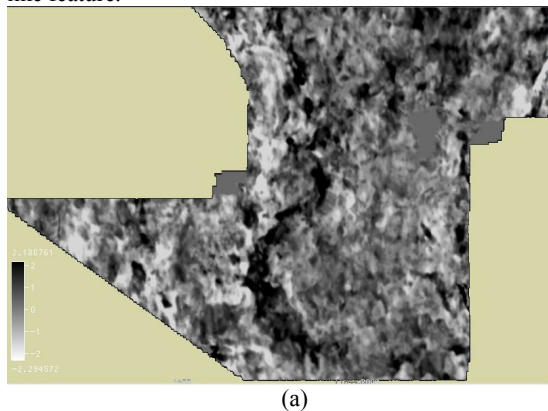


Figure 2 : Seismic data (a) and RMS amplitude attribute (b) on time slice 950 ms, highlighting meandering channel in the area.

The identified channel at time slice 950 ms, is targeted for the present study of unsupervised clustering of seismic data. A horizon close to the reflection near 950 ms is tracked throughout the volume and used for further analysis.

Seismic attributes analysed and used for the present study are shown in the Table 1. Various Amplitude based attributes were applied with optimum parameters to highlight channels in the region of interest and attributes that could able to bring out channel geometry has been selected for the present study.

Haralick et al. (1973) proposed 14 GLCM based statistical measurements, and these 14 statistical measurements can be grouped based on the measures of contrast, orderliness and derived statistics. Selection of GLCM attributes for the present study is given below with the discussion of each group and selected attributes.

a. **Contrast:** Contrast group of attributes are GLCM Contrast, Dissimilarity and Homogeneity. Attributes in this group are influenced by local variations in the analysis window and these attributes are correlated with the amplitude difference and are not sensitive to the mean amplitude value of the analysis window.

GLCM contrast is chosen for the study, due to its response to the channel features. Other attributes are also useful in delineation of channel, but as they are strongly correlated with each other, hence only representative attribute i.e. GLCM contrast is selected from this group, and the same methodology is adapted for selection of attributes in other groups also.

b. **Orderliness:** This group of attributes are GLCM Energy, Entropy and Angular Second Moment, and depends on the measure of orderliness in the analysis window. This set of attributes also not sensitive to the mean amplitude values of the analysis window.

GLCM Entropy and Energy are used from this group for the present study as both provides useful information about orderliness in the analysis window. These two attributes are most used GLCM attributes in the literature for texture based facies analysis.

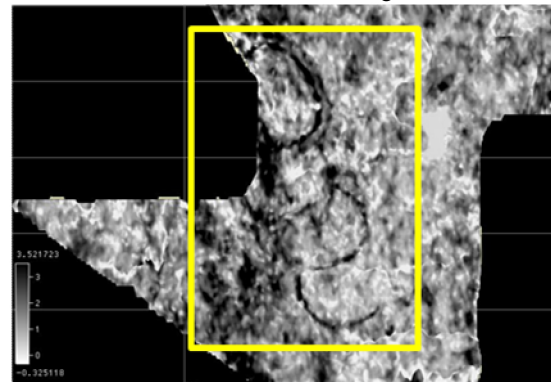
c. **Statistics:** This group consists of GLCM Mean, Variance, Standard Deviation and Correlation attributes. These attributes provide statistical measurement like mean, variance and Standard Deviation from GLCM as defined by Haralick et al. (1973).

GLCM Variance is selected for the present study, which is a measure of dispersion from GLCM mean. GLCM contrast also provides the information about local variance in the analysis window, but these two attributes are not highly correlated to each other. Baraldi et al. (1995) shows that GLCM variance is not dependent on the GLCM Contrast. A high GLCM variance may exhibit high GLCM contrast but the low contrast may exhibit either high variance or low variance.

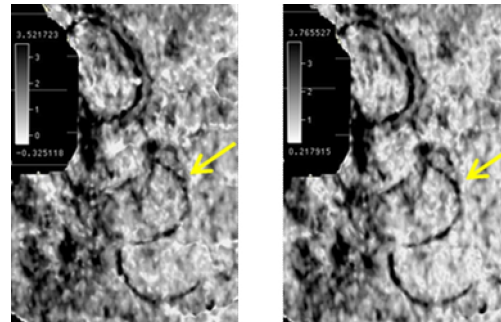
S.No.	Seismic Attribute
1	RMS Amplitude Attribute
2	Instantaneous Attributes
3	Instantaneous Amplitude 1 st & 2 nd Derivative
4	Hilbert (Quadrature Amplitude)
5	Envelope weightage Frequency
6	Envelope Weightage Phase
7	Texture Attributes – Texture Entropy, Energy, Contrast and GLCM Variance

Table 1: List of seismic attributes used for the study.

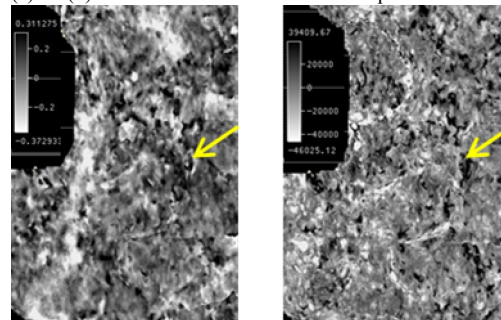
All the selected attributes are applied along the tracked horizon and the results are shown in Figure 3.



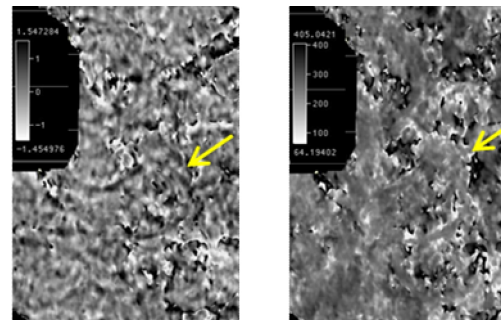
(a) DSMF data along horizon close to 950 ms and highlighted area with yellow is shown in figure parts (b) to (n)



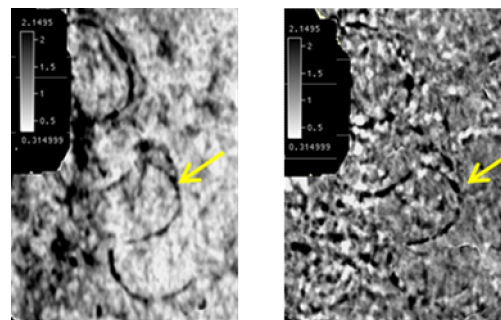
(c) & (d) DSMF data & Instantaneous Amplitude



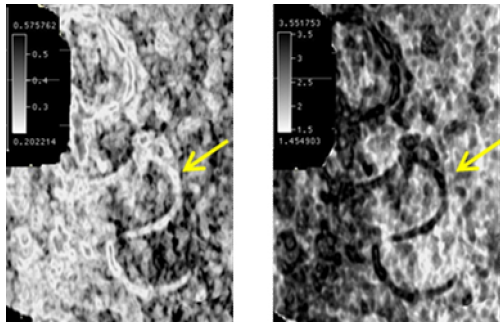
(e) & (f) 1st & 2nd Derivative of Instantaneous amplitude



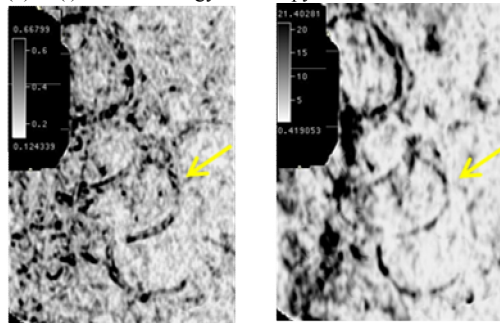
(g) & (h) Envelope Weightage Phase & Frequency



(i) & (j) RMS Amplitude & Hilbert (Quadrature Amplitude).



(k) & (l) Texture Energy & Entropy



(m) & (n) Texture Contrast and GLCM Variance

Figure 3: Application of selected physical attributes are shown in figure from (a) to (j). Channel is visible on the seismic data along the horizon (a). Instantaneous amplitude (c), 2nd derivative of Instantaneous amplitude (f), Envelope weightage phase (g), RMS amplitude (i) and Hilbert Transform clearly highlighted the channel as compared to remaining attributes. Texture attributes (k) to (n) clearly delineated the channel. Yellow arrow pointed visibility of a part of channel through various seismic attributes.

Figure-3 shows the application of chosen attributes along the horizon for delineation of channel. Different attributes illuminate the parts of channel with varying degree. These set of information provided by different attributes can be integrated together for cluster analysis through unsupervised techniques, containing clusters having similar statistical properties.

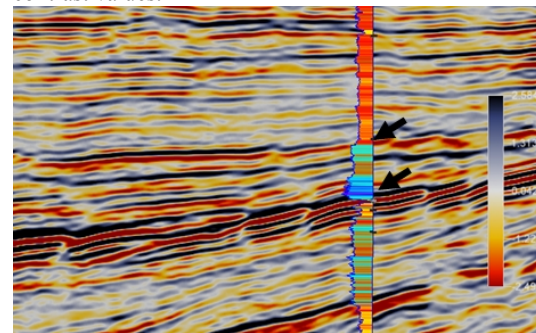
After attribute studies along horizon for delineation of channel, unsupervised waveform segmentation and unsupervised neural network analysis is carried out to cluster and rank of chosen seismic attribute for delineation of channel.

Correlation of Texture attributes with Well Log Data:

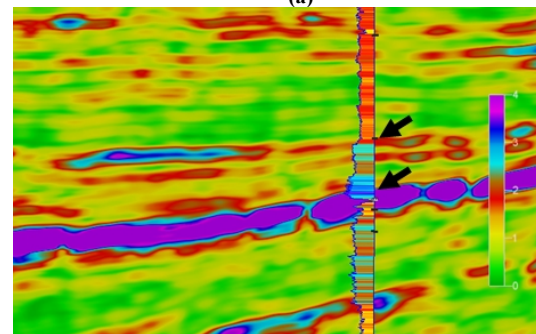
Texture attributes are found to provide good response for delineation of channel as shown in Figure 3. Hence, a study is carried out to see the correlation between used Texture attributes and Gamma Ray Log to understand capabilities of texture attributes to reflect changes in lithology. As, no drilled well passes through the studied channel, hence a

well is chosen from the study area, for calibration of texture attributes.

Gamma ray log data is displayed in Figure-4 on the well location (Scale: low values are towards the well). RMS amplitude attribute (Figure 4.b) shows high values at the location of formation change highlighted by black arrows in Figure-4. RMS attribute exhibits very high values near coal marker. In case of Texture Entropy attribute (Figure 4.c) it also correlated well with the lithology changes and gives high entropy at lithology variation. It also resolves the variation near coal marker which is not clear with RMS behavior as compared to Entropy, and it's able to provide information about lithological variation in the shown inline. Texture Energy exhibit inverse behavior as compared to Entropy, and it's able to provide information about lithology variation in the shown inline. Texture Contrast and GLCM Variance also provide information about lithology variation but information from these attributes is not as clear as Texture Energy and Entropy. Although results from Texture Contrast and GLCM Variance are similar, but there are areas in Figure 4.e and 4.f (highlighted with black rectangles) where high GLCM variance has been observed in the areas of low contrast values.



(a)



(b)

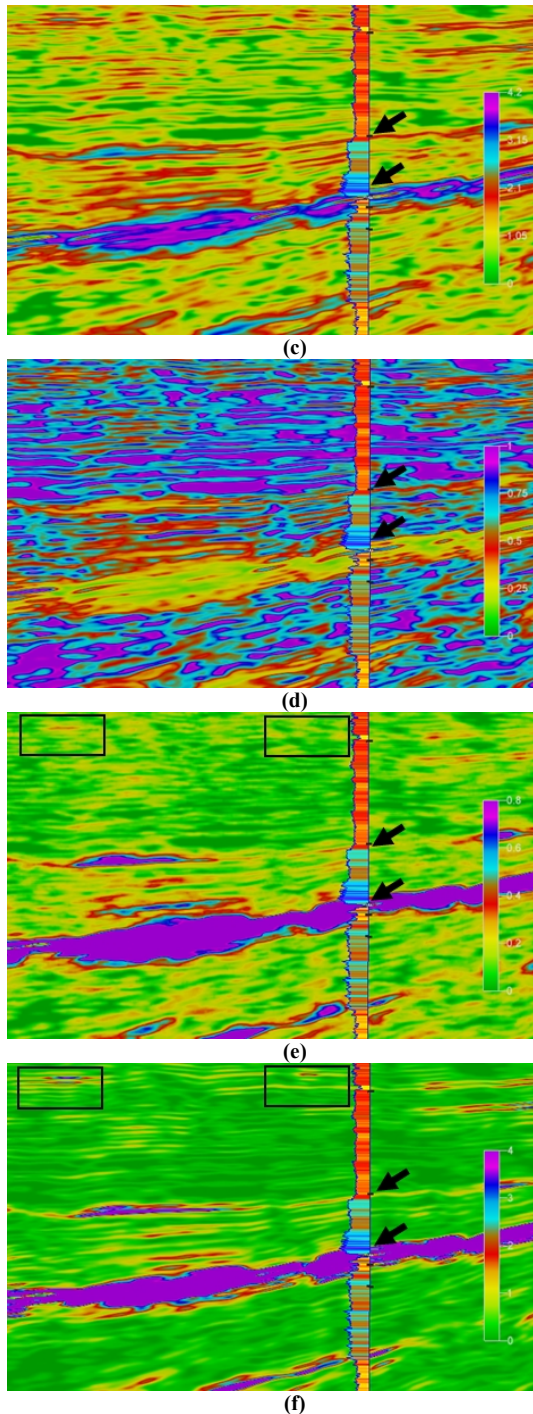


Figure 4: Figure shows (a) Seismic data, (b) RMS amplitude attribute, Texture (c) Entropy, (d) Energy, (e) Contrast and (f) GLCM Variance on Inline through Well with gamma ray log

Correlation of Texture attribute with Gamma Ray Log on the well. Well-chosen is properly tied with seismic using synthetic seismogram approach and then response of Texture attributes are compared with Gamma Ray Log and RMS amplitude attribute.

Unsupervised Clustering of Seismic Data

Seismic waveforms from the same geological features like channels may exhibit similar characteristics. As, shown in Figure-3, seismic response from the channel for different attributes are different, but same attribute like Texture Entropy (3.1) or RMS (3.i) exhibits high values through most part of the channel.

To test the seismic waveform correlation through channel, unsupervised waveform segmentation is performed using Seismic data (DSMF), RMS Amplitude attribute and Texture Entropy Attribute to cluster similar seismic responses in same classes and results are shown in Figure 5 and Figure-6.

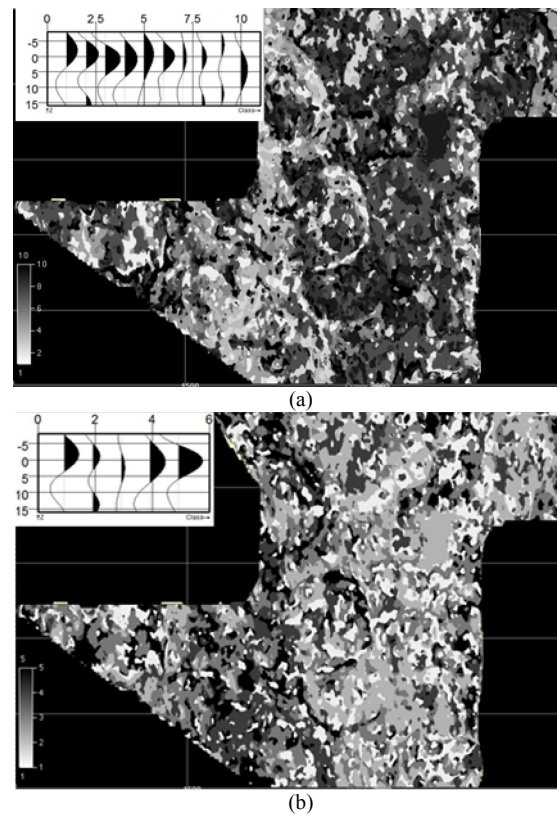
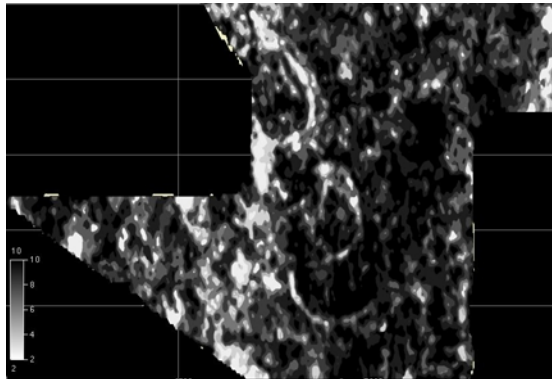
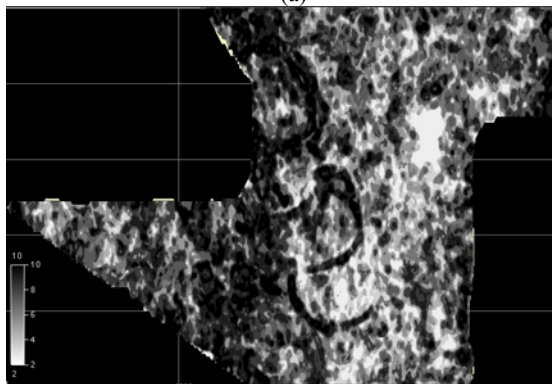


Figure 5: Unsupervised waveform segmentation with different classes (a) 10 classes & (b) 5 classes using seismic data. It can be seen from both the segmentation that, waveform segmentation could able to cluster waveforms related to channel in the same classes.



(a)



(b)

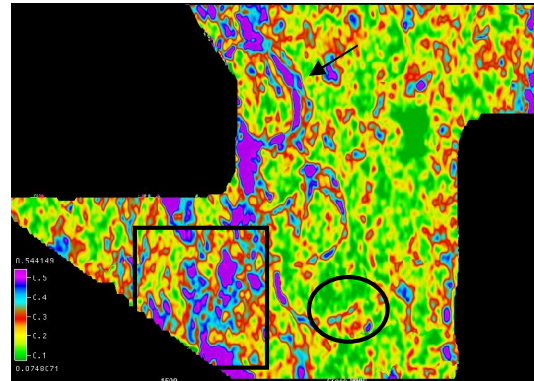
Figure 6: Unsupervised segmentation from RMS amplitude (a) and Texture Entropy attribute (b). Both the segmentation resulted in delineation of channel corresponding to the different classes.

Figure 5 and 6 shows the application of unsupervised segmentation using Seismic data (Figure-5) and Seismic attributes (Figure-6) for delineation of channel. It can be clearly seen from both the figures that seismic attributes are better in clustering of channel related characteristics in same classes as compared to seismic data.

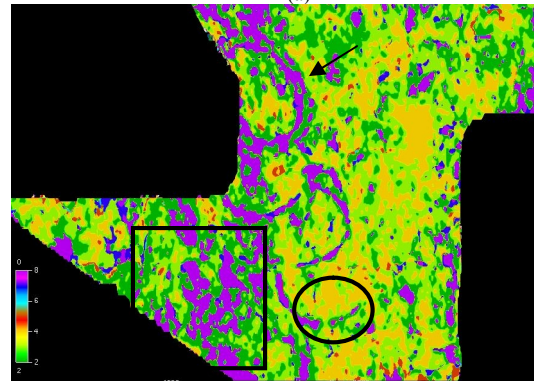
Seismic data and both the attributes are able to cluster the seismic responses or channel in same classes with varying success. Integration of this information may leads to a better clustering for channel delineation. Hence an unsupervised Neural Network clustering algorithm is used for clustering seismic responses to channel and results are discussed in Figure-7. Seismic attributes (Figure-3) which has given good response to channel are used for the unsupervised segmentation study. As, all selected Texture attributes are able to highlight the channel geometry, hence used them for unsupervised segmentation. Used sets of seismic attribute for the study are shown in Table 2. Seed points for unsupervised neural network are generated at the regular grid of 15X15 with 20 ms interval.

S.No.	Seismic Attribute Set – I	Seismic Attribute Set II
1	Seismic Data	Texture Entropy
2	Instantaneous Amplitude	Texture Energy
3	Hilbert (Quadrature Amplitude)	Texture Contrast
4	RMS Amplitude Attribute	Texture GLCM Variance

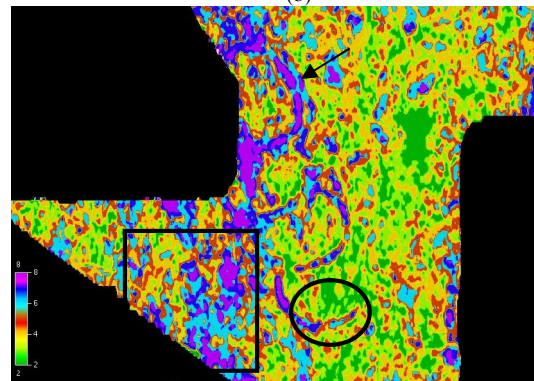
Table 2: List of seismic attributes used for unsupervised segmentation study.



(a)



(b)



(c)

Figure 7: Unsupervised segmentation of seismic attributes for Set-I (b) and Set-II (c) as mentioned in Table 2 in comparison with RMS

amplitude attribute (a). Clustering using Seismic attributes Set-I of Table 2 (b) classified channel part into same clusters. Although it is able to segment seismic responses of channel in same classes, but variance within the channel and nearby areas as highlighted by rectangle as compared to RMS amplitude attribute are missing, which may play important role in characterization of channel fill. Clustering using texture attributes (b) able to delineate channel parts and additional provide insight into the classes with in the channel as well. Texture attribute based clustering also delineated part of channel (highlighted with circle) more clearly as compared to RMS amplitude attribute or segmentation based on the other seismic attributes.

Relative Importance	Segmentation using Seismic Attributes (Set-I)	Segmentation using Texture Attributes (Set-II)
1	Instantaneous Amplitude	GLCM Variance
2	RMS Amplitude	Texture Contrast
3	Envelope Weightage phase	Texture Entropy

Table 3: Relative importance of the seismic attributes for delineation of channels from the unsupervised segmentation study discussed in Figure-7.

Both the unsupervised segmentation studies clustered channels part in the clusters 6 to 8, hence centered values of important attributes for these clusters along with cluster 2 which doesn't correspond to channel are shown in Table 4

Attribute\ Cluster	Cluster 2	Cluster 6	Cluster 7	Cluster 8
Texture Entropy	1.64	3.00	3.37	3.28
Texture Contrast	0.16	0.30	0.63	0.45
Texture GLCM Variance	0.74	10.45	10.48	23.68
Instantaneous Amplitude	1.86	1.07	1.79	3.36
Hilbert (Quadrature Amplitude)	1.63	0.12	-1.05	-2.84
RMS Attribute	1.25	0.82	1.21	2.15

Table 4 : Seismic attributes and central values within clusters 6 to 8 corresponding to the channel and cluster 2 which lies outside of the channel.

Comparison of unsupervised segmentation using conventional seismic attributes and Texture attribute are discussed in Figure 7. Clustering using texture attributes leads to set of clusters with varying information which may be crucial for characterization of the channel fill using more advanced studies like impedance inversion. Table 3, shows the relative importance of attributes in segmentation and Instantaneous Amplitude & GLCM variance are found to be controlling the attribute for clustering.

Table 4 indicates the cluster index values, indicating the cluster 6 to 8 are falling within the channel and similar

clustering are observed in the area at places shown in "square" in Figure-7. Texture attributes have high values within the clusters as compared to other clusters.

The unsupervised segmentation study with Set-I and Set-II has brought out that both sets are able to delineate the channel, but the unsupervised segmentation studies using texture attributes (Set-II) has indicated variations within the channel and also the continuity of the channel is delineated. This indicates that texture attributes can contribute to map the lithological variations within the channel

Conclusions

GLCM based texture attributes are found to extract information required to delineate channel in the study area. As, classification of seismic responses is highly dependent on chosen set of seismic attributes, a comparative study is performed to find out relative importance of attributes and discussed in the text. Clustering of waveforms with unsupervised technique is performed on seismic data and seismic attributes. Waveform segmentation based on seismic attributes is found to be providing better results as compared to amplitude based segmentation. Further, texture attribute based waveform segmentation able to cluster seismic responses from channel in the same classes and performed better as compared to RMS amplitude based segmentation. Neural network assisted unsupervised segmentation of information from different seismic attributes demonstrated that texture attribute based segmentation has clearly delineated the channel geometry, as compared to the Set-I based analysis.

Texture attributes are found to be performing better in all the studies of unsupervised segmentation for delineation of channels.

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