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# Evaluating Performance of Semi-Supervised Clustering with Limited Features for Segmenting Salt Bodies in Seismic Images

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***Abstract:*** *In recent years, major hydrocarbon discoveries have been made by exploring subsalt hydrocarbon plays. Finding a proper model for identifying the salt deposits is great importance for identifying salt-related drilling hazards. To simplify the process of salt body extraction from seismic data and better assess the quality of the extracted salt bodies, an automated system is needed. In this work, we deal with detecting salt bodies in seismic data by using very limited number of features that used for texture-based segmentation along with presenting a hybrid semi-supervised clustering technique. Experiment results have shown that the presented technique provides remarkable accuracy.*

**Keywords—**Semi-Supervised; Clustering; Texture-based Segmentation; Seismic Images; Salt Bodies

## 1. INTRODUCTION

Seismic imaging [1] is an active technique used to illustrate the nature of earth's layers located below the surface of the ground. The resulted seismic data gives the explorationist a lot of details about the geology of the subsurface. Seismic data is collected by using a computerized system that registers different seismic reflection events based on various forms of rocks and fluids located in each layer.

Mainly, there are three types of dimensional seismic data: 2D, 3D, and 4D. The 2D seismic image shows a single slice of the earth's layers while the 3D seismic image shows a volume shape of earth core. Whereas, the 4D seismic data is an extension of 3D seismic image by showing 3D volumes at different times. Fig. 1 illustrates example of different 2D seismic images.

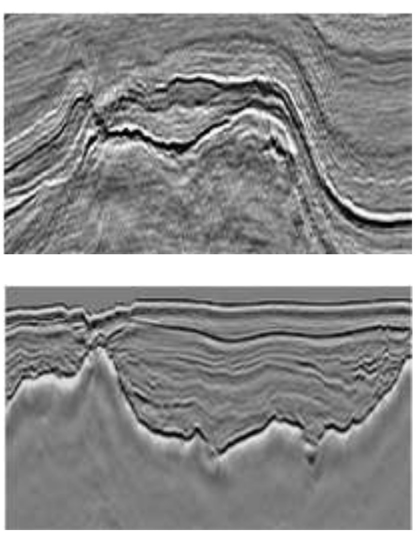

**Fig. 1.** *2D seismic images*

Seismic data is widely used with the field of extracting oil and natural gas. Seismic data help oil and gas companies to improve performance of drilling the earth's layers by selecting optimum locations. Thereby, the extracted amount of oil and gas will be maximized with decreasing the cost. Currently, recent artificial intelligence systems have been employed to explore place of oil and gas. One of the most important tasks achieved by these systems is based on detecting a specific geologic structure in seismic data. This geologic structure is referred to as "salt dome".

Salt dome [2] is a mushroom-shaped diaper formed by the deposition of salt. It is an important geologic structure, because it is common for a salt dome to trap petroleum reservoirs. Detecting salt boundaries in seismic data is a challenging problem because of several reasons. The extraction should allow for the possibility that there are sediments within the salt body. The algorithm of detection must handle complex geometries, e.g., top and base salt should not be limited to surfaces that are single-valued in depth. In addition, the quality of the extracted salt body should be assessed. Thus, that the manual quality control and editing to produce the final result is reduced to a minimum. Fig. 2 demonstrates the shape of salt dome within a seismic image.

The current state of the art in salt body extraction is mainly based on using complex operations. Most of these operations mimic deep learning algorithms for interpreting salt bodies. To simplify process of extracting salt bodies from seismic data with reasonable performance, we present a semi-supervised clustering technique. The presented technique provides remarkable results with a very limited number of features (attributes).

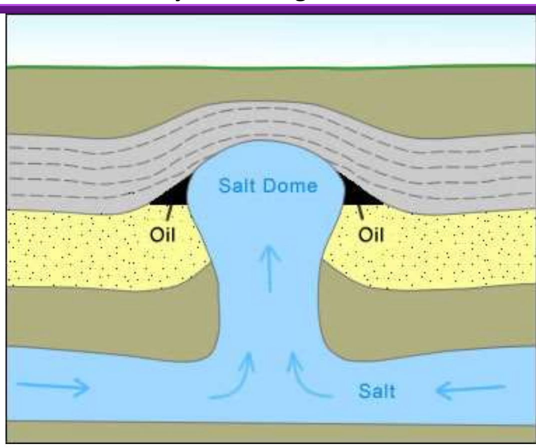


**Fig. 2.** *Salt dome and reservoirs of oil or gas. Reprinted from geology.com*

Our work focuses on segmenting 2D seismic images to detect salt bodies. The main objective of our work is to determine a small set of feature vector to be used for segmentation purposes. In order to extract these pieces of information about the presence of salt structure, we used features that fit texture-based segmentation. In addition, two clustering algorithms (mean shift and k-means) are used to enhance the results.

The rest of paper is organized as follows: Section 2 describes a review for some related studies. Section 3 explains the presented semi-supervised clustering technique. Section 4 discusses the experiment results and provides due analysis. Finally, Section 5 concludes the paper and reveals some suggestions for future work.

## 2. Literature Review

We surveyed two main aspects in order to get our research aim which is related to texture-based segmentation of seismic images. The first aspect leads us to survey several approaches to study and evaluate the texture-based segmentation techniques. The second aspect is to discover available approaches for detecting salt bodies in seismic images.

### 2.1 Texture-based Segmentation

Mignotte [3] presented a segmentation methodology based on a preliminary spatially adaptive non-linear data dimensionality reduction step integrating contour and texture cues. The aim of reduction model is to simplify the segmentation subsequent process by converting an input texture-based image into a noisy color image. As a result of applying their reduction methodology, the process of image segmentation is simplified and the robustness of segmentation process is increased.

Clausi et al. [4] described a design-based method to fuse Gabor filter texture features and co-occurrence probability features. Some conclusions of their work include: (i) the curse of dimensionality does not affect the performance of the segmentation; (ii) Linear normalization of Gabor filtered features removes discriminating information and reduces the capability of these features to perform segmentation accurately; (iii) Feature reduction is not expected to improve the segmentation accuracy.

Additionally, circular Gabor filters derived from Gabor elementary functions are analyzed and implemented by Kaur et al. [5]. The authors used wavelet transform techniques in order to implement texture segmentation. The performance evaluation of circular Gabor filters method is optimal in the sense that the resulting prefilter maximizes the ratio of expected average output energy for the two textures.

Three texture attributes are analyzed and described by Berthelot et al. [6]. These attributes include: (i) GLCM attributes, frequency-based attributes, and dip and similarity attributes. In order to test the classification performance, different combinations of the presented attributes are tested by applying a supervised Bayesian classification method. The evaluation results show that the classification performance improved by combining at least two texture attributes.

### 2.2 Salt Dome Detection

Haukås et al. [7] proposed and developed an automated tool in order to extract the body of the salt dome based on level set algorithms. Attributes such as salt boundary attributes and gradient of the seismic data are used to separate between salt and sediments. Discriminating between completed boundary parts and uncompleted ones is implemented using a stop criterion. The proposed methodology of salt body extraction has potential to greatly reduce time spent on salt interpretation, and improve the quality of the seismic data.

Two methods are proposed by Pitas et al. [8] for seismic segmentation and region growing. The first one is based on applying Voronoi tessellation with mathematical morphology. While, the second method is based on using radiation model. Texture and Hilbert transform features are analyzed for describing the texture of seismic images. The used features include length, reflection strength and geometrical appearance.

Some works, most closely related to our research direction, employ data clustering [9] for detecting salt bodies in seismic images. For example, Di et al. [10] used k-means clustering algorithm with a suite of seismic attributes (features) for delineating the surface of salt bodies from 3-D seismic data. Another important work [11] employs Kuwahara filters and multiattribute clustering algorithms to delineate mass transport complexes and salt domes in seismic images.

Moreover, there is another research direction based on employing supervised learning for detecting salt bodies in seismic images. For example, Milosavljevic [12] and Al-Duri et al. [13] employed deep learning for seismic images interpretation. In the same manner, Alfarhan et al. [14] presented an improved UNet architecture for detecting salt domes and faults in seismic surveys.

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## 3. METHODOLOGY

Three texture attributes have been used to achieve our research objectives. The selected attributes are adopted from work archived by Hegazy et al. [15]. These attributes include: (i) Directionality; (ii) Edge content; and (iii) Smoothness. Because of the fact that the textures of salt domes in seismic images lack specific directionality, we can segment the salt dome as follows:

For each data point or pixel, we execute the gradient intensity values in a small square window surrounded the pixel. We compute the gradient of intensity for each pixel the window. Then, a scattered plot of the x and the y gradient components is generated. Finally, the texture of the non-salt region exhibits strong directionality, while that of the salt region lacks it. The eigenvalues of the moment of inertia tensor is used to determine the texture directions as follows:

Let L1[x,y], L2[x,y] denote the eigenvalues of I[x,y]. The directionality attribute at pixel [x,y] is defined as:

$$D[x,y] = 1 - \frac{\min(\Lambda_1[x,y], \Lambda_2[x,y])}{\max(\Lambda_1[x,y], \Lambda_2[x,y])} \tag{1}$$

I[x,y], which is the moment of inertia for the scattered plot, can be computed as:

$$I[x,y] = \sum_{[i,j]\in W_{x,y}} \begin{bmatrix} (G_y[i,j]-\bar{G}_y)^2 & (G_x[i,j]-\bar{G}_x)(g_y[i,j]-\bar{G}_y) \\ (G_x[i,j]-\bar{G}_x)(G_y[i,j]-\bar{G}_y) & (G_x[i,j]-\bar{G}_x)^2 \end{bmatrix}$$

(2)

Where Wx,y is a neighborhood window centered around pixel [x,y], Gx[i, j] and Gy[i, j] are the gradient at a given pixel [i, j], and G'x and G'y are the mean of the x and y components of the gradient computed over the neighborhood window Wx,y.

In many seismic images, the texture of the non-salt dome region seems to have lack of directionality. Thus, the smoothness attributes are implemented in order to complement the directionality attribute in differentiating salt regions. In other words, the smoothness attribute helps eliminating regions that are too smooth to be considered part of a salt region. The following computations are used to compute the smoothness attribute:

$$S[x,y] = -\sum_{[i,j]\in W_{x,y}} |G[i,j]| \tag{3}$$

Where |G[i, j]| is the magnitude of the gradient at pixel [i, j]:

$$|G[i,j]| = \sqrt{(G_x[i,j])^2 + (G_y[i,j])^2} \tag{4}$$

The quality of detected salt dome is affected by edge-like appearance where the non-salt dome is confused with salt dome when the previous attributes (e.g. directionality and the smoothness) are used. Thus, the edge content attribute helps eliminating rough regions that actually belong to edges and not a salt body dome. The edge content attribute can be computed as follows:

$$E[x,y] = \max_{[i,j]\in W_{x,y}} |G[i,j]| - \min_{[i,j]\in W_{x,y}} |G[i,j]| \tag{5}$$

In order to enhance the results of texture-based segmentation we cluster the extracted attributes by using two clustering methods: (i) mean shift clustering [16]; and (ii) k-means clustering [17]. We use k-mean algorithm to cluster a three dimensional data that consists of the three texture attributes. We also use mean shift clustering to segment an image that is generated by individually extracting each texture attribute. Then, we compared the results provided by segmenting seismic images with the three attributes. Finally, we combined the two clustering methods to get the best results.

As a result of this work, a hybrid semi-supervised clustering technique has been presented by combining two phases. Firstly, the image generated by using texture attribute is segmented by using mean shift algorithm. Then, we apply data clustering to the output by using k-mean algorithm with considering the labels (salt / non-salt) used with each cluster. Thereby, the presented technique can be accomplished by passing through different stages as shown in Fig. 3.

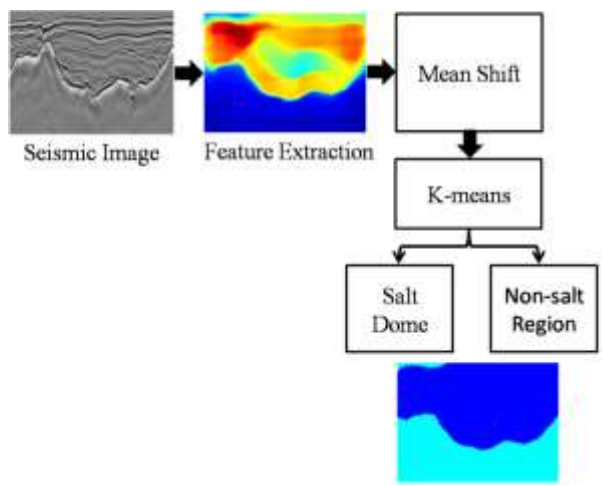
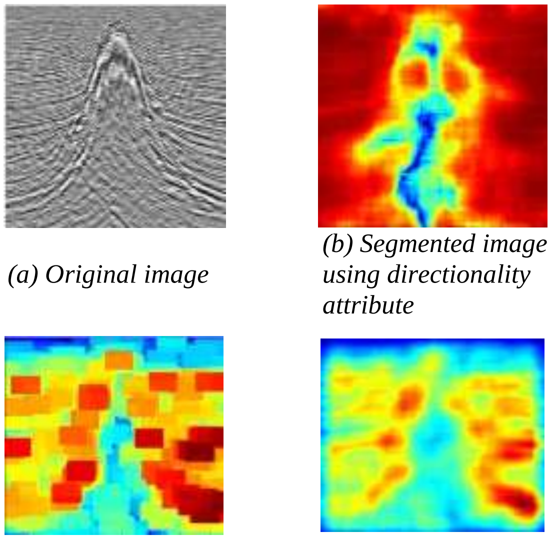



**Fig. 3.** *The presented hybrid semi-supervised clustering technique*

## 4. EXPERIMENT RESULTS AND ANALYSIS

The main objective of this research work is to detect salt dome region in seismic images. In order to achieve this objective, we have used a subset of the real seismic dataset acquired from the Netherland's offshore, F3 block in the North Sea, whose size is 24×16 km2 [18]. For the testing purpose in this work, we selected some 2D seismic images from the used dataset. The selected images contain multiple salt domes as well as the associated structural/depositional features. All experiments are conducted by using Matlab.

Several major components and tasks are applied to detect the salt dome regions. Fig. 4 shows the results of applying the texture based-segmentation method on a seismic image that contain salt dome. Our results show that texture-based segmentation is an encouraging method that can be used to detect salt dome in seismic images. The quality of detected salt dome in images (b and c) which used the edge content attribute and smoothness attribute respectively is better than the ones in (a) which used directionality attribute.



*(a) Original image* *(b) Segmented image using directionality attribute*

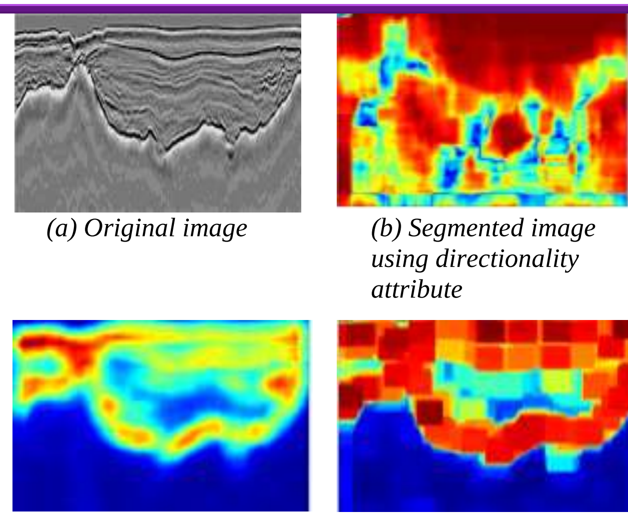
*(c) Segmented image using edge content attribute* *(d) Segmented image using smoothness attribute*

**Fig. 4.** *Texture-based segmentation*

Fig. 5 shows the results of applying the same method i.e. texture based-segmentation but with different image. We can see that the edge content attribute and smoothness attribute are the best attributes in order to detect the salt dome, while the directionality attribute is the worst one. This makes sense because the texture in salt regions lacks specific directionality.

Fig. 6 shows the result of clustering 3-dimensional data (three attributes) of extracted features by using k-means clustering technique. We can see from the figure that the size of the mask affects the detection process. Using small mask size as in (b), (c) and (d) will not detect the “correct” salt dome completely. While, the large size of mask will affect the detection of the salt dome as in (g). Thus, selecting proper mask size, as in (e) and (f), will detect the correct salt dome in seismic images.

We also applied the mean shift segmentation on the images resulted from extracting the texture attributes in order to enhance the quality of detecting salt dome region. We can see from Fig. 7 that applying mean shift segmentation after segmented the images using the smoothness attributes as in (d) gives the best results.



*(a) Original image* *(b) Segmented image using directionality attribute*

*(c) Segmented image using edge content attribute* *(d) Segmented image using smoothness attribute*

Fig. 5. Texture-based segmentation

Moreover, we applied the k-means segmentation on the output resulted from mean shift segmentation (shown in Fig. 7). As shown in Fig. 8, using the smoothness attribute gives the best results (Fig. 8. d) and using directionality attribute gives the worst results. Thus, we can conclude that we cannot use directionality attribute alone when detecting the salt dome because it only finds the degree of changing in gradient directions. On the other side, we can use only smoothness attribute to get good results in detecting salt dome regions. We can also say that using edge content attribute in detecting salt dome regions gives intermediate results in comparison with using directionality and smoothness attributes.

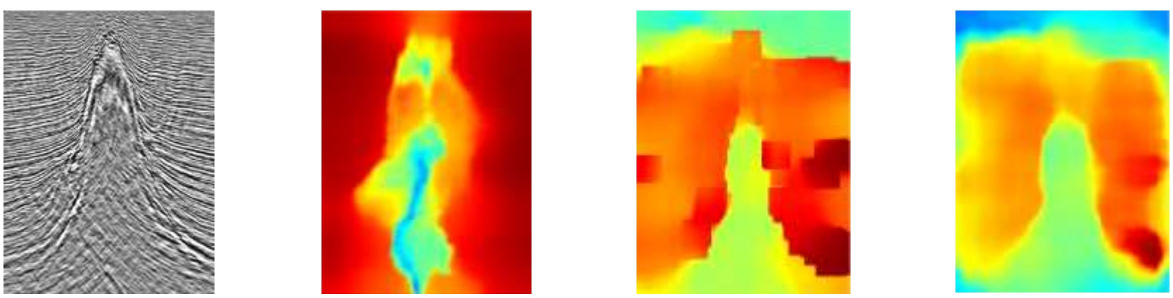
Fig. 9 shows the results of segmenting a seismic image by using the presented technique (mean shift followed by k-means segmentation). As shown in the figure, the results are changed when changing the mask size into 11, 13 and 15. Thereby, the presented is sensitive to the mask size. Thus, we need to select the best value of mask size to get the best results of detecting the salt dome for each seismic image.

To compare performance of the presented technique with other related works, we evaluated performance of applying graph-based segmentation. We applied two common graph-based segmentation models: Adjacent neighborhood model and K-nearest neighborhood model. Fig. 10 shows the results of these two models. We can see that the presented technique provides competitive results in comparison with graph-based segmentation.

*(a) Original Image* *(b) Mask size = 5* *(c) Mask size = 9* *(d) Mask size = 11* *(e) Mask size = 13*

*(c) Mask size = 15* *(c) Mask size = 36*

**Fig. 6.** *K-means segmentation using different mask sizes*

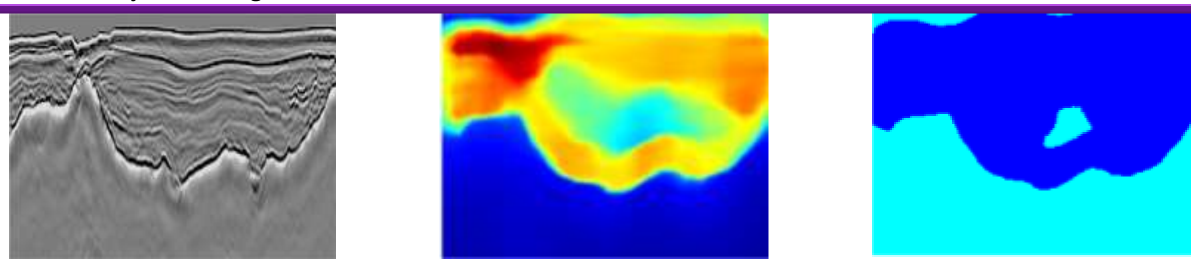


*(a) Original Image* *(b) Directionality attribute* *(b) Edge content attribute* *(d) Smoothness attribute*

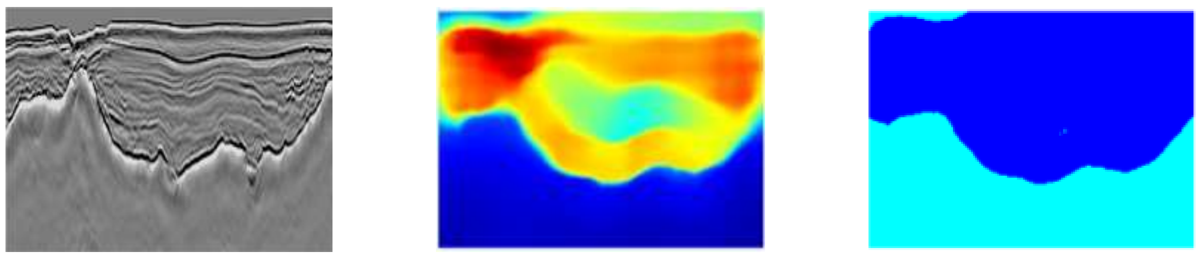
**Fig. 7.** *Applying mean shift segmentation with different texture attributes*

*(a) Original Image* *(b) Directionality attribute* *(b) Edge content attribute* *(d) Smoothness attribute*

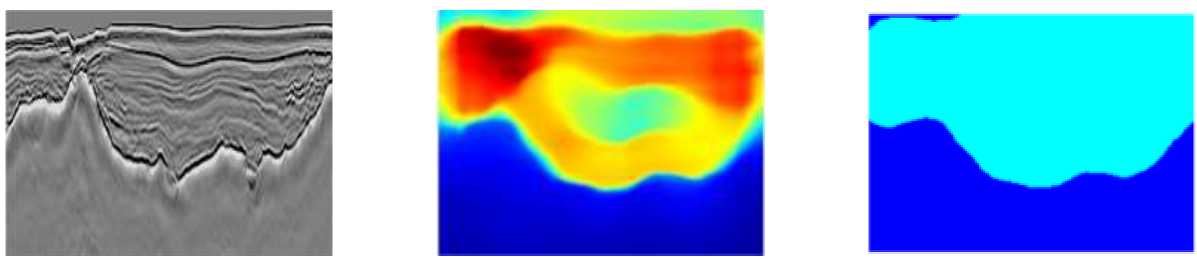
***Fig. 8.*** *Applying mean shift segmentation followed by k-means segmentation on the images resulted from extracting different texture attributes*



*(a) Original seismic image* *(b) mean shift (Mask size = 11)* *(c) K-means (Mask size = 11)*

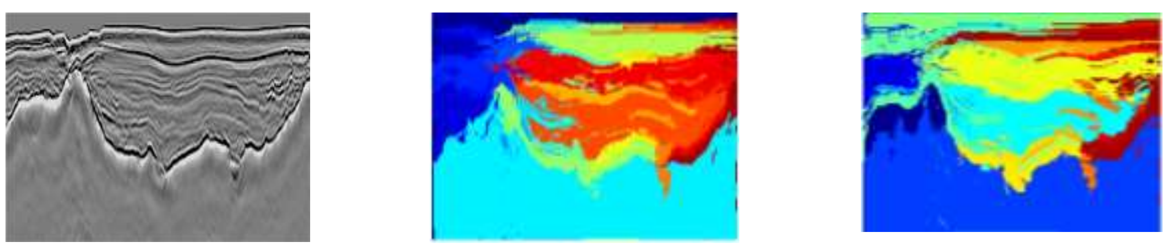


*(d) Original seismic image* *(e) mean shift (Mask size = 13)* *(f) K-means (Mask size = 13)*

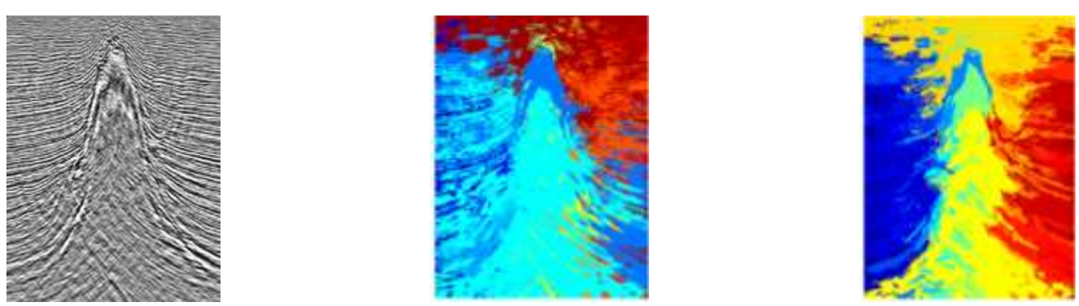


*(g) Original seismic image* *(h) Mean shift (Mask size = 15)* *(i) K-means (Mask size = 15)*

**Fig. 9.** *Applying mean shift segmentation followed by k-means segmentation with changing the mask size*



*(a) Original seismic image* *(b) Adjacent neighboring* *(c) K-nearest neighborhood*



*(d) Original seismic image* *(e) Adjacent neighboring* *(f) K-nearest neighborhood*

**Fig. 10.** *Graph-based segmentation using two models*

## 5. Conclusion and Future Work

In this research work, we present a technique for detecting salt bodies in seismic images. The presented technique is based on using semi-supervised clustering with very limited features. Our findings conclude that the presented technique, which mimics texture-based segmentation, provides competitive results in comparison with graph-based segmentation.

Performance of the presented technique encouraged us to extend this work by evaluating performance of applying more segmentations methods along with supervised and semi-supervised learning. It will be also interested to evaluate performance of using more texture features.

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