Salt Dome Detection Using Context-Aware Saliency

Abdulmajid Lawal*, Qadri Mayyala†, Azzedine Zerguine* and Azeddine Beghdadi‡
*Electrical Engineering Department, Kind Fahd University of Petroleum & Minerals, Dhahran, 31261, Saudi Arabia
g201403800@kfupm.edu.sa, azzedine@kfupm.edu.sa
†Department of Electrical and Computer Engineering, Birzeit University, Birzeit, Palestine
qmayyala@birzeit.edu
‡L2TI, Institut Galilée, Université Sorbonne Paris Nord, 93430 Villetaneuse, France
azeddine.beghdadi@univ-paris13.fr

***Abstract*—This work presents a method for salt dome detection in seismic images based on a Context-Aware Saliency (CAS) detection model. Seismic data can easily add up to hundred of gigabytes and terabytes in size. However, the key features or structural information that are of interest to the seismic interpreters are quite few. These features include salt domes, fault and other geological features that have the potential of indicating the presence of oil reservoir. A new method for extracting the most perceptual relevant features in seismic images based on the CAS model is proposed. The efficiency of this method in detecting the most salient structures in a seismic image such as salt dome is demonstrated through a series of experiment on real data set with various spatial contents.**

I. Introduction

The use of imaging techniques of complex geological structures for petroleum and gas prospecting is one of the most recently established applied research in geophysics. However, seismic images are often of bad quality and rather difficult to interpret. Their processing and analysis require the use of increasingly sophisticated algorithms to reduce uncertainties in the interpretation. Petroleum and natural gas can be trapped by the salt due to its impermeable properties [1]. Hence, detecting salt dome presents high potential of locating oil and petroleum reservoir. Detecting such structures is still a challenging problem. The ever increasing size of seismic data is compelling a shift from manual labelling to automatic labelling. This is due to the time cost and intensive labour involved in manual labelling. Different authors from both industry and academics have proposed image processing tools and deep learning based approaches for mitigating this problem [2]–[4]. However, due to the low quality of the captured signal and the enormous amount of information to be analyzed, automatic detection of salt domes is a real challenging problem.

In the past decades, several researchers proposed different approaches for detecting subsurface structures using perceptual and learning approaches [3], [5], [6]. Some of the other works include the use of graph theory, edge detection, texture normalized graph cut, active contours and other tools [7], [8]. Given the appearance of the structures to be extracted from the images, one would be tempted to use directional band-pass filters such as Gabor filters [9], or the generalized Hough transform [10] which allows to highlight curvilinear structures. Unfortunately, these two solutions are not easy to adapt to this context given the high density and multi-directional aspect of the boundaries of the different layers in seismic images. This is also the case for other classical and appealing approaches such as generalized Hough transform and even multi-centered Hough Forest method [8].

This is what motivated us to move towards approaches based on perceptual aspects. Indeed, the extraordinary ability of the Human Visual System (HVS) to perceive and extract structures of varying spatial frequencies and in various directions has inspired many biologically-inspired methods in image processing and analysis [11]. The main idea in the proposed work is to exploit the way the HVS extracts the relevance perceptual information from an observed scene. One key concept in visual perception is what is called ”Visual Saliency” (VS). Modeling such characteristic of the HVS is rather a complex task.

Some models have been proposed in the literature. Itti et al's model [12] is one of the most complete and well-known VS models. The VS in its broad sense can mean different things and in particular any attractive feature on the physical, psycho-visual or informational level in a general way. It is one of the perceptual characteristics of the HVS that provides useful information for understanding visual attention interactions with observed scenes. It could be used to highlight the relevant areas in the image for various applications, such as image watermarking [13], image quality assessment [14], or inpainting forgery detection [15], to name a few. The HVS reduces the amount of information gathering that has to be processed by focusing on the salient part of the visual information. There are several VS models in the literature [16].

It is worth noticing that the VS has been used in very few published works related to seismic image analysis. In [17], the VS combined with other traditional seismic attribute has been used in order to detect faults in seismic sections. A 3D FFT VS-based approach for detecting salt dome bodies in seismic volume has been proposed in [1].

In this paper, we propose a salt dome detection method in seismic images based on the concept of Context-Aware Saliency (CAS) introduced in [18]. The model is based on both local and global consideration and has been applied successfully in retargeting and summarization of natural images. The proposed model is based on four principles related to the psychology of vision, namely local low-level aspects such as contrast and colour, global considerations, spatial organization laws derived from Gestalt theory laws and high-level factors.

In the proposed method for salt dome detection in gray-level seismic images, we limit the model to the most relevant perceptual features and restrict the analysis to the local-low level factors such as contrast and pixel/patch gray-level at different scales. We also consider the global aspects so as to remove irrelevant local features while maintaining global salient features.

The details of the proposed method and the adaptation of the CAS concept to our specific application are presented in Section II. Section III is dedicated to the performance evaluation of the proposed method. Finally, the paper ends with a brief conclusion and some perspectives.

II. Proposed Method

The proposed method operates according to a sequential scheme consisting of four essential and interdependent steps. First, the CAS map of the input seismic volume image is computed. Note that here, we restrict the CAS map computation method to the first main steps as described in [18]. In the second step, the obtained CAS map is thresholded in order to classify pixels into two categories, namely regions with salt boundary with high saliency values and regions without salt boundaries corresponding to low saliency values. In the next step, morphological filtering is performed on the thresholded image to remove noise and smoothen the salt boundaries. Finally, the thresholded image is skeletonized in order to extract the salt boundary as a one-pixel-thick piecewise curvilinear structure.

In the ensuing, the main steps of the proposed method are described and discussed.

A. *Simplified aware-context saliency model*

The underlying idea of CAS based detection [18] in the case of seismic data is that salient regions in seismic images are distinctive in both local and global surrounding. It is worth noticing that areas containing perceptual salient patterns exhibit high saliency level. Whereas, homogeneous and blur zones exhibit low saliency level. Moreover, frequently occurring features are not considered as relevant and consequently suppressed. In contrast, pixels with high saliency levels are grouped together. This is in line with the nature of salt dome boundary which is often unique and continuous along the seismic image.

If now we analyse the image at different scales by using sliding patches, each pixel i is associated to a patch at a scale r. The idea of using a multi-resolution patch allows to track the salient features at different levels [19]. Then, a pixel i is considered as salient if the associated patch is perceptually very different from the other patches. To explain the concept of CAS in the case of seismic images, we follow the same approach used in [18]. For the sake of completeness and clarity, we use the same notations and concepts.

Let us consider $d_{gray}(p_i, p_j)$ denoting the similarity measure between the two gray-level patches p_i and p_j. A pixel i is considered as salient if $d_{gray}(p_i, p_j)$ is high for all image patches p_j. In the case of seismic images, for every patch p_i, it is more appropriate to limit the search space to the K perceptual nearest patches $\{q_k\}_{k=1}^{K}$. Hence, p_i is perceptually far from all the other patches if the perceptual nearest patches are highly different from it. Then, the search space is limited to the K perceptual nearest patches $\{q_k\}_{k=1}^{K}$ according to the metric $d_{gray}(p_i, p_j)$. Therefore, a pixel i is salient if $d_{gray}(p_i, q_k)$ is high beyond certain threshold $\forall\ k \in [1, K]$. It is worth noticing that the model should consider both the distance between patches and the perceptual grouping as important aspects when extracting the salient patches. Similar approach based on the bilateral filtering has been proposed for image denoising in [20]. Indeed, it is observed that the background patches look similar to other patches both near and far away in the seismic image. Whereas, similar patches tends to be perceptually grouped together. Therefore, a patch p_i is considered as salient if the perceptually nearest patches are also geometrically close to it. Let $d_{position}(p_i, q_k)$ denotes the Euclidean distance between the patches p_i and q_k. By taking into account both distances (geometric and perceptual) between the two patches a dissimilarity metric is defined as

$$d(p_i, q_k) = \frac{d_{gray}(p_i, p_j)}{1 + c.d_{position}(p_i, q_k)}. \tag{1}$$

Note that, the geometrical distance is normalized by the larger image aspect dimension. From equation (1) it can be noticed that the dissimilarity metric is directly proportional to the perceptual distance and inversely proportional to the geometric distance. Here, the parameter c controls the balance between the two distances and is set experimentally to 4. Other sophisticated distance weighting functions could be used as done in [20]. Finally, a pixel i is considered salient if $d(p_i, q_k)$ is beyond certain value $\forall\ k \in [1, K]$, (K=32 in our experiment). Hence, the single-scale saliency value of pixel i at scale r is defined as

$$S_i^r = 1 - exp\left[\frac{-1}{K}\sum_{k=1}^{K} d(p_i^r, q_k^r)\right]. \tag{2}$$

The multi-scale aspect is incorporated to better discriminate the various spatial frequency contents in the image. This is because background patches are likely to have similar pixel at different multiple scale in a homogeneous seismic image while the salient pixels have similar patches at a few scale but not all. This in turn improves the contrast between the salient and non salient regions. In other words, a pixel is considered salient if it is consistently different from other pixels at multiple scales.

Let us consider a patch p_i at scale r and all the other patches whose scales are $R_q = r, \frac{1}{2}r, \frac{1}{4}r$. Among all this patches, the K most perceptual similar patches according to (1) are found and used for the computation of the multiscale CAS map. The visual saliency map S_i^r at each scale is then normalized to the gray-level interval [0,1]. Therefore, each pixel is represented by a set of multiscale seismic image patches centered at it. Then, let $R = \{r_1, ..., r_M\}$ denote the set of patch sizes associated with pixel i. The saliency at pixel i is then taken as the mean of its saliency at different scales, that is,

$$\bar{S}_i = \frac{1}{M} \sum_{r_i \epsilon R} S_i^r, \tag{3}$$

where S_i^r is given by (2). Note that high saliency value of pixel i corresponds to large $\bar{S}_i$ and high dissimilarity values in various levels to the rest of the patches. In the implementation, the seismic images are rescaled to same size of 192×512 pixels each. The saliency of all the pixels is then computed. A patch of 7×7 is employed to search for the nearest neighbors with halve overlaps which has been found to be more effective than other patch sizes. Here, we use the scales $R = \{100\%, 75\%, 50\%, 25\%\}$ as done in [18].

B. Salt dome detection

Once the CAS map is computed, the seismic image is decomposed into two classes of pixels according to the saliency values. This is based on the fact that the non salt region has a lower saliency value $\bar{S}_i$ relative to the salt boundaries. The saliency map is then thresholded using the following rule:

$$B_T(i) = \begin{cases} 0, & if \quad \bar{S}_i \leq T, \\ 1, & otherwise. \end{cases} \tag{4}$$

B_T represents the binary image where the white region within the binary image is the region that is likely to contain salt boundaries. T corresponds to the threshold value which is obtained by the gray-level thresholding method proposed by Otsu [21]. The reason for using Otsu's image binarization algorithm is its superiority over many sophisticated methods in terms of simplicity and efficiency. The thresholded image contains some spurious structures and irregular forms. Indeed, salt dome by its nature may have complex structures corresponding to noise and disconnected regions. Morphological operation is then applied to eliminate the noise and spurious structures. Specifically, both morphological closing and dilation are performed with a circular disk with a radius set to the value 40 after several tests on different images. In the final stage, skeletonization is performed on the saliency map to obtain the salt boundary. This is one of the main advantage of this method. In the other method, the saliency map is only used to highlight the saltdome region, however in this method, the saliency map is further processed to extract the final one-pixel-thick structure.

III. Experimental Results and Discussion

In this section, we present the results of the proposed method on a publicly available real seismic dataset acquired from Netherlands offshore, F3 block in the north sea. A typical seismic inline section extracted from this dataset containing salt dome region is shown in Fig 1. The salt dome boundary is characterized by subtle intensity variations, which makes it extremely challenging and difficult to detect.

The subjective evaluation of the presented results shows that the proposed method highlights and detects salt dome efficiently. While majority of the algorithms only apply saliency for higlighting the salt dome region, the proposed method goes one step further by using the available saliency map to detect the boundaries of the salt dome region. Figure 2 shows the obtained saliency map. It can be observed that the salt boundaries is the region with high pixel values while the other region has low pixel values, hence less bright. This shows the usefulness of saliency map in highlighting the boundaries.

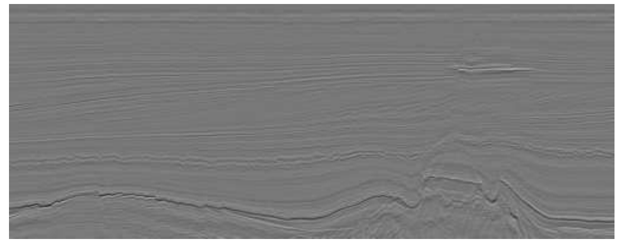

Fig. 1. Original seismic image before processing.

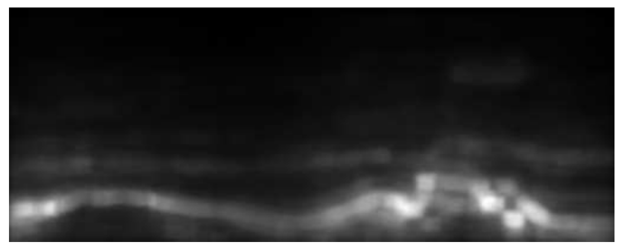

Fig. 2. The saliency map obtained from the original image.

In Fig. 3 we displayed an overlaid CAS map on the original image. The region, where the CAS map is high, corresponds to the salt boundaries while the other pixels correspond to the background in the seismic image.

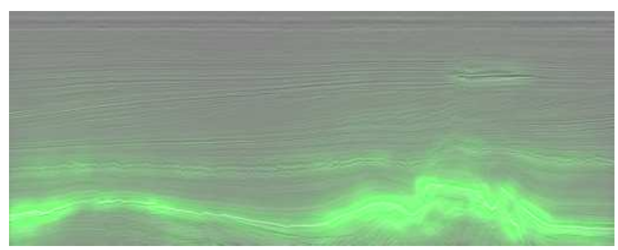

Fig. 3. Overlaid saliency map highlighting the salt boundaries and important geological parts of the image.

In the next stage of the algorithm, the saliency map is thresholded then filtered by morphological operations to remove the noise and small clusters that are not considered to be part of the salt boundaries but yet salient. Figures 4 and 5 illustrate the thresholded CAS map and the overlaid thresholded version on the original image, respectively. It can be observed that after thresholding and performing the morphological operations, the derived map is mainly covering the salt boundaries.

In the final stage, we further processed the saliency map using skeletonisation to obtain the main boundary. Figures 6 and 7 show the skeletonized map of the thresholded map and the overlaid map on the original image, respectively. It can be

Fig. 4. The thresholded saliency map with only the salt boundaries.

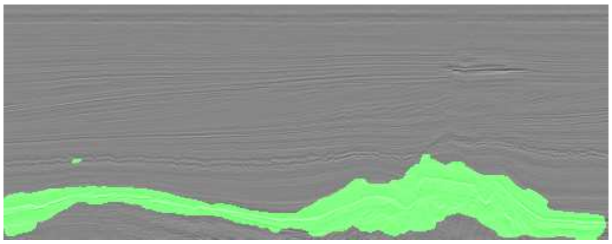

Fig. 5. The thresholded saliency map overlaid on the original image highlighting only the salt boundaries.

noticed that the detected boundaries fit well the contours of the salt dome region as shown in the original image.

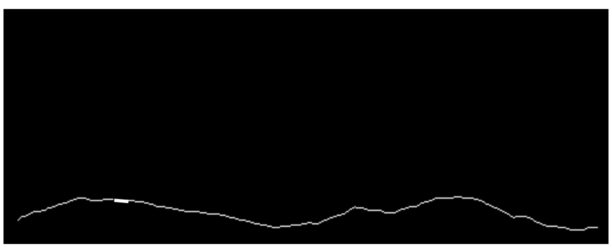

Fig. 6. The sekeletonized saliency map to highlight the salt boundaries.

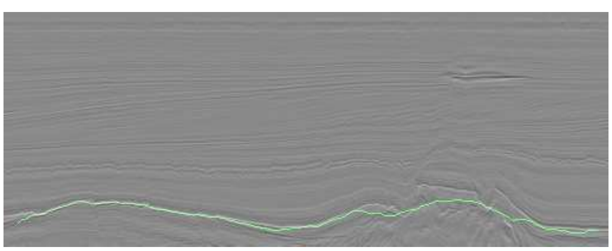

Fig. 7. The skeletonized saliency map overlaid on the original image to highlight the salt boundaries.

To further test the robustness of the proposed approach, we applied it to different inlines (seismic section), inline 164 and 200 as shown in Figures 8 and 9. It is noticeable that the detected boundaries match quite well with the ground truth. This clearly demonstrates the efficiency of the proposed approach in detecting the boundaries of salt dome regions.

Finally, Figures 10 and 11 provide a subjective comparison between the proposed approach on seismic inline section 429 and 459, respectively, and other existing approaches. While the magenta, yellow, cyan, blue represent the methods in [22], [23], [24], [25], respectively, the black represents the proposed approach and the red represents the ground truth. Once again it can be seen that the proposed approach is much closer to the ground truth.

The proposed method is implemented in MATLAB on core-i7 CPU PC with 8GB RAM. While the approach in [1] took 30 seconds to run, the proposed method took 33 seconds. However, the proposed method is less noisy and has a better resolution. Due to space limitation the subjective evaluation of all the obtained results is not included. It is important to note that the proposed method may fail in case of multiple boundaries or complicated boundary structures. This is one of the aspect we will consider in a future work.

IV. Conclusion

In this paper, we proposed a novel context awareness saliency-based method for highlighting and detecting salt boundaries in seismic images. The proposed scheme is capable of reducing the amount of time spent in detecting salt boundaries in seismic images. Unlike other methods that only use saliency to highlight the salt boundaries, this technique is capable of detecting the salt boundaries. The method may be modified further for capturing faults and horizons in seismic volumes. The experimental analysis shows that the proposed approach can accurately highlight and detect salt boundaries which eases the interpreters work, reduces time and improves efficiency. The tuning of the relevant parameters using a learning based approach would be one of our future work. Another important aspect that could be considered in a near future is the building of a database with ground truth and objective measures to quantify the quality of the extracted structures.

Acknowledgment

The authors acknowledge the support provided by the Deanship of Scientific Research at KFUPM under Research Grant **SB181001**.

References

[1] M. A. Shafiq, T. Alshawi, Z. Long, and G. AlRegib, "Salsi: A new seismic attribute for salt dome detection," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1876–1880, IEEE, 2016.

[2] A. D. Halpert, R. G. Clapp, and B. Biondi, "Seismic image segmentation with multiple attributes," in *SEG Technical Program Expanded Abstracts 2009*, pp. 3700–3704, Society of Exploration Geophysicists, 2009.

[3] H. Di, Z. Wang, and G. AlRegib, "Deep convolutional neural networks for seismic salt-body delineation," in *AAPG Annual Convention and Exhibition*, 2018.

[4] W. Wang, F. Yang, and J. Ma, "Automatic salt detection with machine learning," in *80th EAGE Conference and Exhibition 2018*, 2018.

[5] M. A. Shafiq, Z. Long, T. Alshawi, and G. AlRegib, "Saliency detection for seismic applications using multi-dimensional spectral projections and directional comparisons," in *2017 IEEE International Conference on Image Processing (ICIP)*, pp. 455–459, IEEE, 2017.

[6] J. Cao, Y. Yue, K. Zhang, J. Yang, and X. Zhang, "Subsurface channel detection using color blending of seismic attribute volumes," *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 8, no. 12, pp. 157–170, 2015.

[7] N. Drissi, T. Chonavel, and J. M. Boucher, "Salient features in seismic images," in *OCEANS 2008-MTS/IEEE Kobe Techno-Ocean*, pp. 1–4, IEEE, 2008.

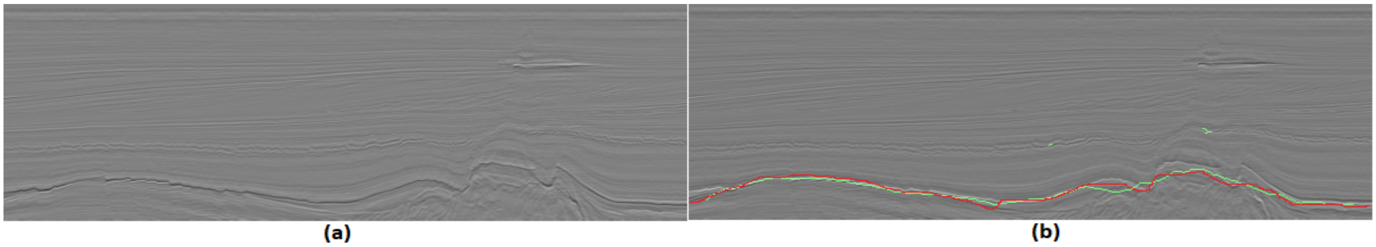

Fig. 8. The original seismic section inline number 164 and the detected boundary (in green) and the ground truth (red).

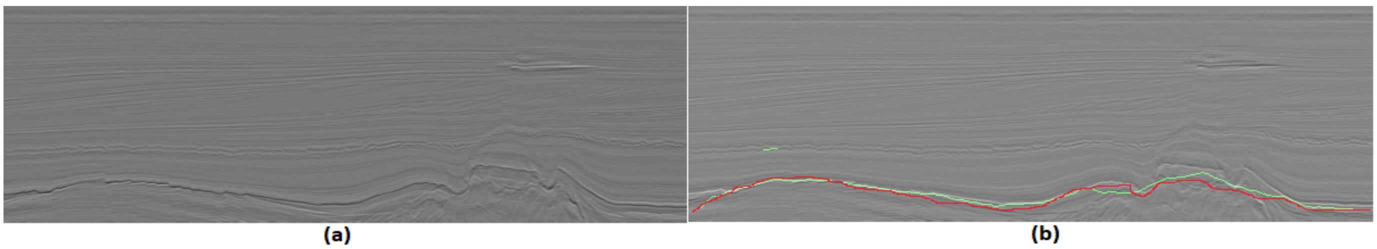

Fig. 9. The original seismic section inline number 200 and the detected boundary (in green) and the ground truth (red).

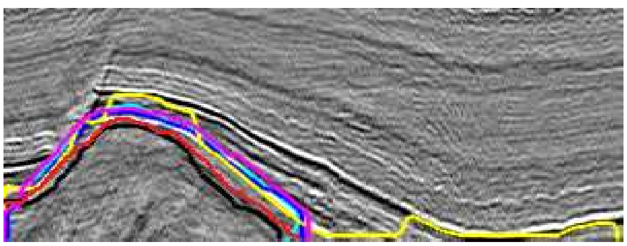

Fig. 10. The proposed and compared with other methods. Magenta: [22], Yellow: [23], Cyan: [24], Blue: [25], Black: The proposed, red: Ground Truth

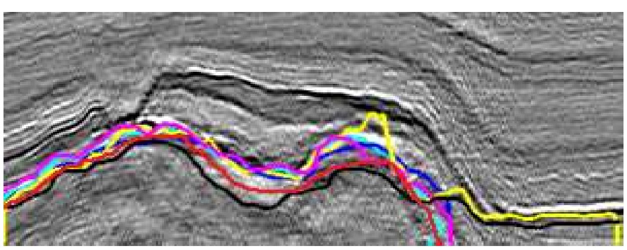

Fig. 11. The proposed and compared with other methods. Magenta: [22], Yellow: [23], Cyan: [24], Blue: [25], Black: The proposed, red: Ground Truth

[8] H. Zhang, Y. Yang, and H. Shen, "Detection of curvilinear structure in images by a multi-centered hough forest method," *IEEE Access*, vol. 6, pp. 22684–22694, 2018.

[9] D. A. Clausi and M. Ed Jernigan, "Designing gabor filters for optimal texture separability," *Pattern Recognition*, vol. 33, pp. 1835 – 1849, 2000.

[10] D. H. Ballard, "Generalizing the hough transform to detect arbitrary shapes," *Pattern Recognit.*, vol. 13, no. 2, pp. 111–122, 1981.

[11] A. Beghdadi, M.-C. Larabi, A. Bouzerdoum, and K. M. Iftekharuddin, "A survey of perceptual image processing methods," *Signal Process. Image Commun.*, vol. 28, no. 8, pp. 811–831, 2013.

[12] L. Itti, C. Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 11, pp. 1254–1259, 1998.

[13] Y. Niu, M. J. Kyan, L. Ma, A. Beghdadi, and S. Krishnan, "Visual saliencys modulatory effect on just noticeable distortion profile and its application in image watermarking," *Signal Processing: Image Communication*, vol. 28, no. 8, pp. 917–928, 2013.

[14] T. T. Dang, A. Beghdadi, and M.-C. Larabi, "Perceptual quality assessment for color image inpainting," in *IEEE International Conference on Image Processing, ICIP*, Melbourne, Australia, September 15-18, 2013, pp. 398–402, 2013.

[15] D. T. Trung, A. Beghdadi, and M.-C. Larabi, "Blind inpainting forgery detection," in *IEEE Global Conference on Signal and Information Processing, GlobalSIP 2014*, Atlanta, GA, USA, December 3-5, 2014, pp. 1019–1023, 2014.

[16] R. Cong, J. Lei, H. Fu, M. Cheng, W. Lin, and Q. Huang, "Review of visual saliency detection with comprehensive information," *IEEE Trans. Circuits Syst. Video Techn.*, vol. 29, no. 10, pp. 2941–2959, 2019.

[17] A. Lawal, S. Al-Dharrab, M. Deriche, G. Alregib, and M. Amir Shafiq, "Fault detection using seismic attributes and visual saliency," in *SEG Technical Program Expanded Abstracts 2016*, pp. 1939–1943, Society of Exploration Geophysicists, 2016.

[18] S. Goferman, L. Zelnik-Manor, and A. Tal, "Context-aware saliency detection," *IEEE transactions on pattern analysis and machine intelligence*, vol. 34, no. 10, pp. 1915–1926, 2012.

[19] D. T. Trung, M.-C. Larabi, and A. Beghdadi, "Multi-resolution patch and window-based priority for digital image inpainting problem," in *3rd International Conference on Image Processing Theory, Tools and Applications (IPTA) 2012*, pp. 280–2084, 2012.

[20] Q. B. Do, A. Beghdadi, and M. Luong, "Image denoising using Bilateral filter in high dimensional patch-space," in *European Workshop on Visual Information Processing, EUVIP 2011*, Paris, France, July 4-6, 2011, pp. 36–41, 2011.

[21] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Trans. Sys. Man. Cyber.*, vol. 9, no. 1, pp. 62–66, 1979.

[22] A. A. Aqrawi, T. H. Boe, S. Barros, *et al.*, "Detecting salt domes using a dip guided 3d sobel seismic attribute," in *2011 SEG Annual Meeting*, Society of Exploration Geophysicists, 2011.

[23] A. Berthelot, A. H. Solberg, and L.-J. Gelius, "Texture attributes for detection of salt," *Journal of Applied Geophysics*, vol. 88, pp. 52–69, 2013.

[24] Z. Wang, T. Hegazy, Z. Long, and G. AlRegib, "Noise-robust detection and tracking of salt domes in postmigrated volumes using texture, tensors, and subspace learning," *Geophysics*, vol. 80, no. 6, pp. WD101–WD116, 2015.

[25] M. A. Shafiq, Z. Wang, A. Amin, T. Hegazy, M. Deriche, G. AlRegib, *et al.*, "Detection of salt-dome boundary surfaces in migrated seismic volumes using gradient of textures," in *2015 SEG Annual Meeting*, Society of Exploration Geophysicists, 2015.