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(Research Article)

Gas Reservoir Detection Using Mixed Components Short Time Fourier Transform (MC-STFT) as a new attribute

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Abstract

Identification of gas reservoirs as a main natural resource due to their economic importance has always been one of the most important issues in research studies in the oil and gas fields. Accurate localization of a gas reservoir through seismic data has been broadly studied. The final destination of all seismic attributes is to distinguish a specific feature. Accordingly, many seismic attributes have been developed, among which short-time Fourier transform (STFT)-based methods play an important role. The location of gas reservoirs can be detected, taking advantage of its particular criteria in seismic data. Generally, seismic signals are non-stationary as their frequency responses vary with time. Thus we propose an attribute that utilizes mixed components of STFT (MC-STFT). The novelty about this method is that without altering STFT method or adding any complexity, MC-STFT is able to detect gas reservoirs at high resolution. Simplicity and time efficiency can make a method superior. In fact, this method takes advantage of extracting three frequency components obtained by STFT. In the next step, we can do the second iteration of the procedure, this will represent the degree of sharpness of reduction in amplitude and again do the same jobs as before and it leads to this, making it more specific. We apply this method to three data sets, first, Marmousi model and then two other real seismic zero-offset sections. To evaluate the proposed method compared with the Synchrosqueezing STFT (SSTFT). The results confirm the good performance of MC-STFT in high-resolution gas reservoir detection.

Keywords: Gas reservoir, STFT, Seismic data, Attributes, Localization.

1. Introduction

The location of gas reservoirs can be detected using its particular criteria in seismic data. Generally, seismic signals are non-stationary as their frequency responses vary with time. There are some techniques called Time-Frequency Decomposition (TFD) which map a 1D signal into a 2D plane of time and frequency. In this way, the frequency content of the signal with respect to time can be revealed. Therefore, TFD methods are used as spectral decomposition in both seismic processing and interpretation (Reine et al., 2009; Chen et al., 2014). For example, Partyka et al., (1999) adopted the windowed discrete Fourier transform (DFT) for reservoir characterization. To detect low-frequency shadows beneath hydrocarbon reservoirs, Castagna et al. (2003) applied the matching-pursuit decomposition. Sinha et al. (2005) proposed a novel method of taking a Fourier transform of the inverse continuous wavelet transform (CWT) as a time-frequency map to identify subtle stratigraphic features (Zhang et al., 2019). Wu and Yatong (2018) developed a synchrosqueezing wavelet transform (SWT) to reallocate the wavelet transform values to different points and produce a sharp spectral decomposition for the input signal (Mateo et al., 2020). Li and Xiaodong (2008) took advantage of the smoothed pseudo-Wigner-Ville distribution (SPWVD) for carbonate reservoir characterization. Lu & Qiang (2009) applied the deconvolutive short-time Fourier transform (DSTFT) method, which improves the time and frequency resolution of the STFT spectrogram by 2D deconvolution on seismic spectral decomposition. Liu et al. (2011) proposed a spectral decomposition method in which time-varying Fourier coefficients are used to define a time-frequency map (Zhuang et al., 2020).

Spectral decomposition has been applied in

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exploration fields such as hydrocarbon detection, seismic attenuation analysis, channel identification, and thin-layer thickness estimation (Quan & Jerry, 1997; Gao et al., 1999; Lu & Fangyu, 2013; Zhou et al., 2019; Odegard et al., 1997). Conventional spectral decompositions have some restrictions such as the Heisenberg uncertainty principle and cross-terms which limit their applications in signal analysis. In an effort to overcome some of the limitations, the STFT has been used (Siddique et al., 2023; Yang et al., 2019). Recently, valuable efforts have been made to cover these limitations, Barabadi et al. (2024) used synchroextracting transform for AVO analysis in time frequency, and Shirazi et al. (2023) employed Multi-synchrosqueezing transform to detect shallows gas.

In this article, we propose a novel seismic attribute to detect gas reservoirs, which is based on STFT (Cohen, 1989). The superiority of this method relies not only on its simplicity (which does not add any mathematical burden to the STFT method), but also on the high-resolution characterization it provides. This method takes advantage of seismic low-frequency shadows as a gas reservoir indicator. The novelty behind this algorithm is in the seismic signal transformation from the time domain to the time-frequency domain using STFT and then extraction of three frequency sections of each signal. This approach converts the seismic zero-offset section into a 2D image of the gas reservoir.

We assess the performance of the proposed algorithm against three models including the Marmousi model and the other two real data. The results show that the first iteration of this algorithm can locate gas reservoirs at high resolution, which can also be much more accurate by applying the second iteration in comparison to the method SSTFT.

2. Theory

2-1. Short Time Fourier Transform (STFT)

This section first deals with the STFT formulation used in this study and then the STFT-proceeding algorithm to obtain the final gas reservoir image.

The discrete-time STFT method is formulated as:

$$X_{STFT}[m,\omega] = \sum_{n=-\infty}^{\infty} x[n]\, w[n-m] e^{-i\omega n} \quad (1)$$

$$w(m) = a e^{-\frac{(m-b)^2}{2c^2}} \quad (2)$$

where $w(m)$ is the window function (which is Gaussian in this study). In the Gaussian window, a is the height of the curve's peak, b is the position of the center of the peak, and c is the standard deviation. m and ω are discrete time shift and angular frequency, respectively, and $x[n]$ is the seismic signal.

2-2. Mixed Components of STFT (MC-STFT)

The STFT of $x[n]$ can be interpreted as the Fourier transform of the product $x[n]w[n-m]$. Thus as it is clear, in this study, there are no changes in the STFT formulation. The next step is to extract three frequency component sections from the time-frequency domain obtained by applying STFT on each seismic trace.

$$\begin{cases} the\ first\ (f)\ component = C_1(m, f_1), \quad f_1 = {F_N}/{10} \\ the\ second\ (f)\ component = C_2(m, f_2), \quad f_2 = {F_N}/{5} \\ the\ third\ (f)\ component = C_3(m, f_3), \quad f_3 = {F_N}/{3} \end{cases} \quad (3)$$

where F_N is the Nyquist frequency of seismic signals. Now, these frequency components are normalized so that the effect of intensity of each frequency will be the same. Therefore, they are denoted by $C_{1,N}$, $C_{2,N}$ and $C_{3,N}$. The final step is to multiply these component sections as below and get the final image.

$$G(m, d_i) = (C_{1,N} * C_{2,N} * C_{3,N})_i \quad (4)$$

where $G(m, d_i)$ is the final gas reservoir image, and d_i is the horizontal distance in seismic zero-offset section (i.e. the ith trace). To obtain a more accurate gas reservoir location, we can do the second iteration of this procedure. The first and the second iterations are summarized as shown in the Table 1.

Table 1. The algorithm of the first and the second iterations of the method.

	$k = 1, \quad first\ iteration$
1-	$x_i[n]$, $as\ the\ ith\ trace\ of\ zero - offset\ section$
2-	$X_{STFT,\,i,\,k}[m, f] = STFT(x_i[n]\,)$
3-	$extracting\ C_{1,\,N,\,k}, C_{2,\,N,\,k}\ and\ C_{3,\,N,\,k}$
4-	$G_{k,\,i}(m) = (C_{1,\,N,\,k} * C_{2,\,N,\,k} * C_{3,\,N,\,k})_i$
	$k = 2,\ second\ iteration$
5-	$G_{k-1,\,i}(m),\ as\ the\ ith\ signal\ of\ gas\ image\ section$
6-	$X_{STFT,\,i,\,k}[p, f] = STFT(G_{k-1,\,i}(m))$
7-	$extracting\ C_{1,\,N,\,k}, C_{2,\,N,\,k}\ and\ C_{3,\,N,\,k}$
8-	$G_{k,\,i}(p) = (C_{1,\,N,\,k} * C_{2,\,N,\,k} * C_{3,\,N,\,k})_i$

2.3. Synchrosqueezing STFT (SSTFT)

The SSTFT is a combination of the STFT and the synchrosqueezing method. The synchrosqueezing method is used to sharpen the STFT map, and therefore, generates a concentrated time-frequency map named SSTFT (Auger et al., 2013).

The SSTFT is given by:

(5)

Where

$$w_k - w_{k-1} = (\Delta w)_k \qquad (6)$$

This is the forward transform. The energies of the STFT are squeezed to the instantaneous frequency locations according to Equation (5) in order to get a concentrated time-frequency representation.

3. Results and Discussion

In this study, we assess the performance of the proposed algorithms (i.e. both first and the second iteration). We do this with three models, first with a real well-known Marmousi model then two other real models.

3-1. Marmousi Model

This model is a 3500 m of depth and 17000 m of distance in which there are some gas reservoirs (figure 1). We picked one of these reservoirs to test out the algorithm. As shown in Figure 1, there is a gas reservoir on the top left of this geological section (Martin et al., 2006). Therefore, we cropped the original section, which is the pre-stack depth migration image of the area (Figure 2), from 1875 m to 6250 m in distance and from 0 s to 1.37 s in time (Figure 2). The cropped section (Figure 3) is then used to apply our algorithm. The result of applying the first iteration of MC-STFT in this section leads to locating the gas reservoir but there is still an anomaly at the water bottom (Figure 4a). Other anomalies but the gas reservoir will be attenuated by the second iteration (Figure 4b). As it is clear from Figure 4b, the second iteration eliminates the water bottom effect and just gas reservoir anomaly can be seen. The result of SSTFT in figure 4c shows good performance of it, however, the MC-STFT confirms its power to localize the gas reservoir zone.

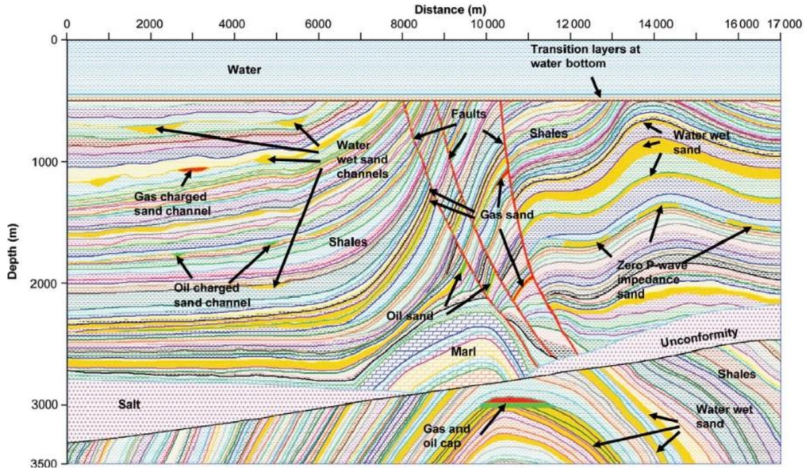


Figure 1. Marmousi model, structural elements, horizons and lithologies.

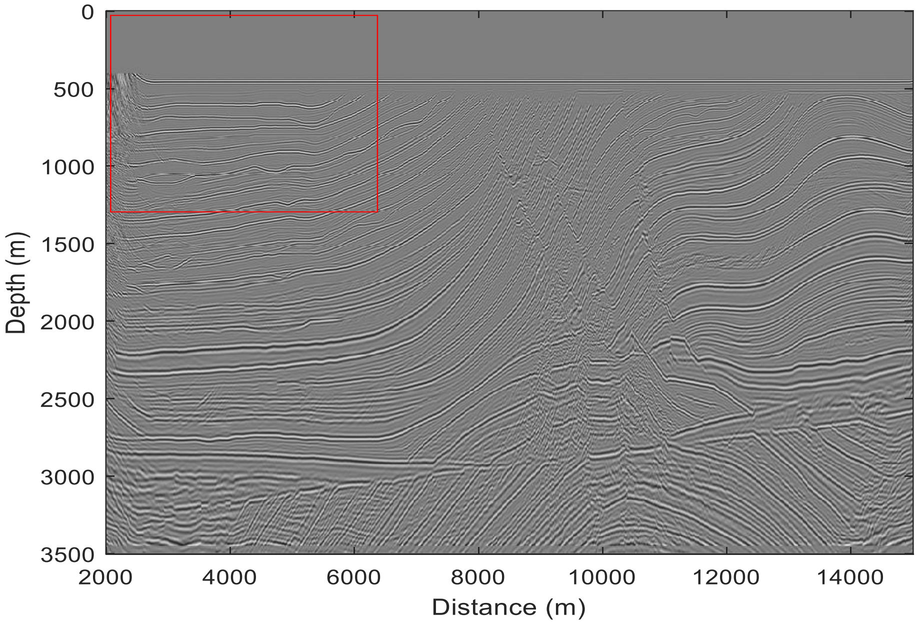


Figure 2. Marmousi zero-offset section (the red box shows the cropped part).

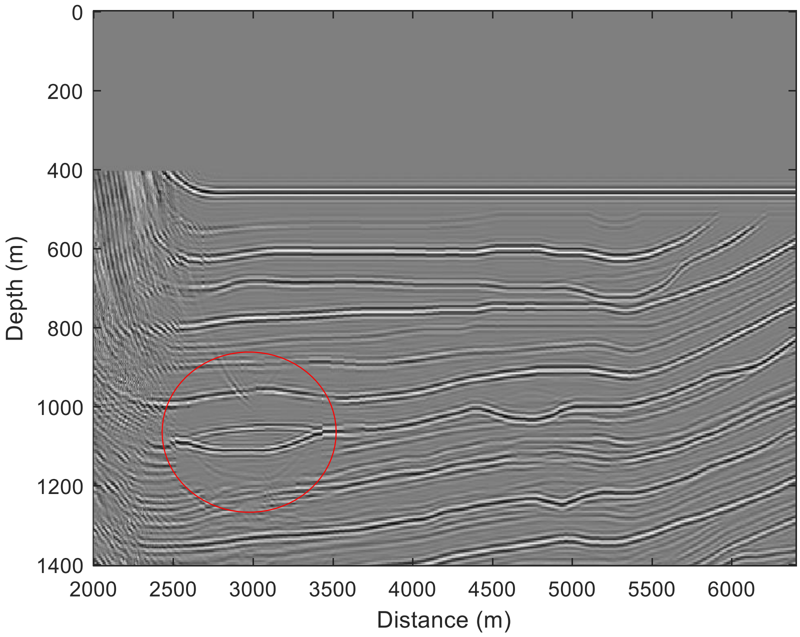


Figure 3. Marmousi cropped zero-offset section (the red circle represents the gas reservoir).

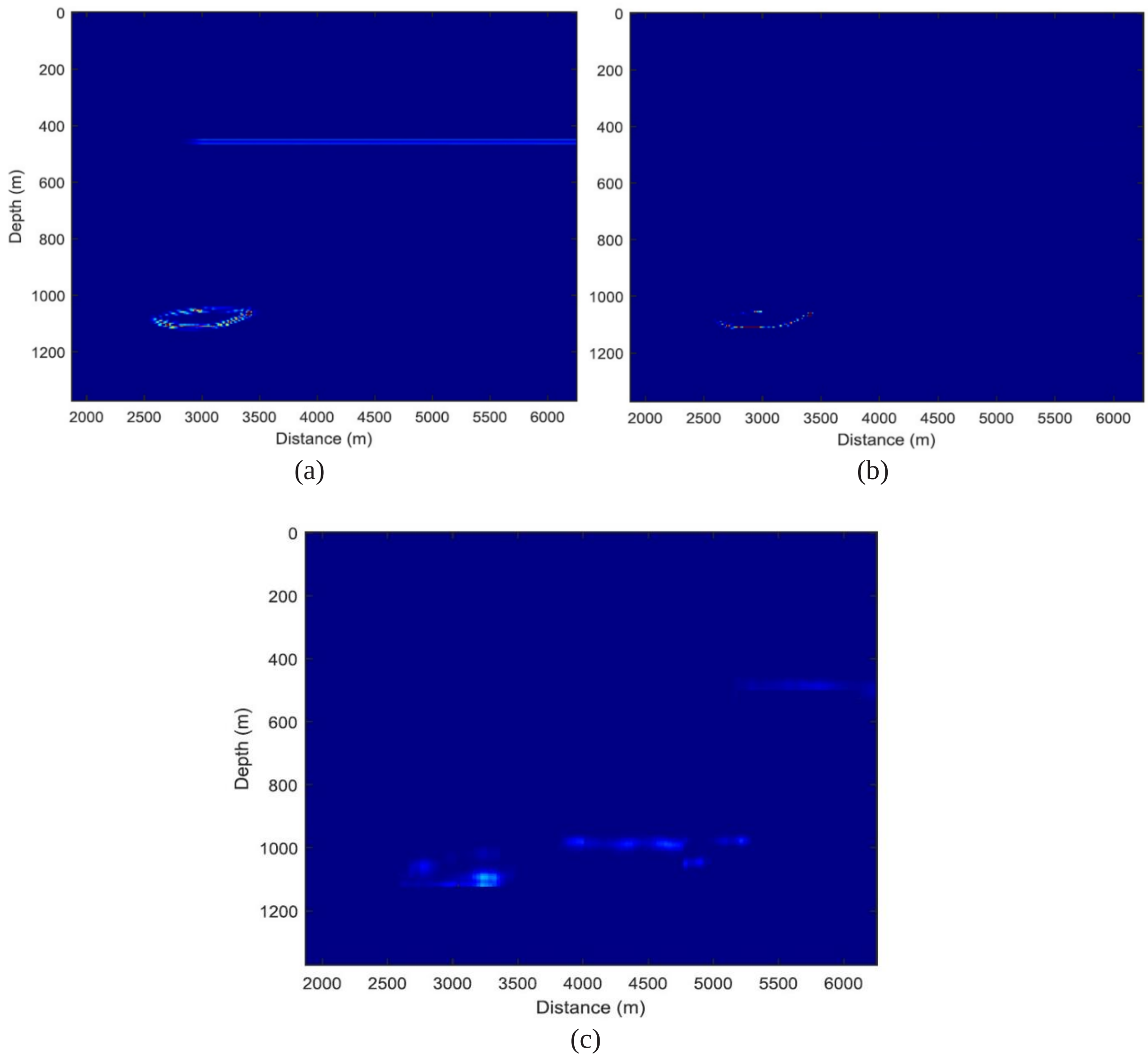


Figure 4. a) The first iteration of MC-STFT. Anomaly shows gas reservoir. b) The second iteration of MC-STFT. c) The result of SSTFT.

3-2. Real model 1

This model is a zero-offset section with 996 ms of the time axis and 1310 m of distance (Figure 5). There is a gas reservoir in this model, which is shown by the red circle. The first and the second iterations of the proposed algorithm are applied in this section. The first iteration bolds the gas reservoir in such a way that there is an anomaly in the gas area (Figure 6a). Although there are still some slight anomalies in other parts of the section, for example, other anomalies can be seen at the bottom of the section. However, the peak of the amplitudes lies in the gas area. The second iteration, on the other hand, located the gas reservoir more accurately and increased the detection resolution (Figure 6b). Figure 6c shows the output of SSTFT, the good performance of which is clear but not the same as the second iteration of MC-STFT.

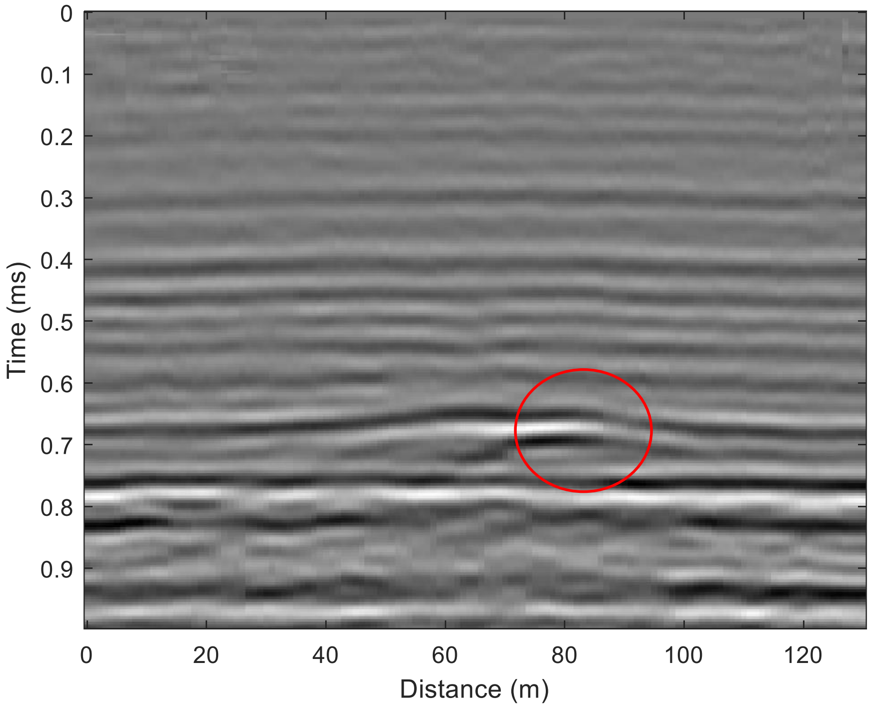
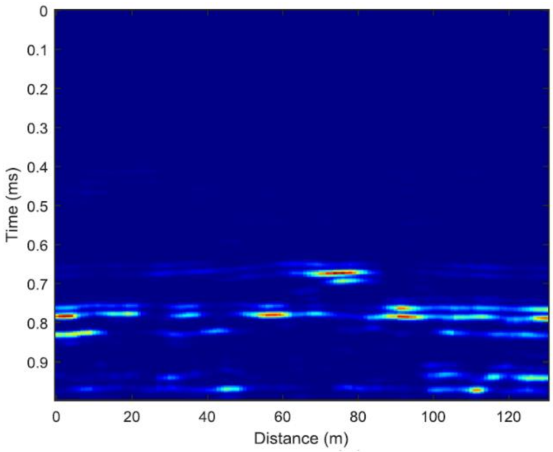
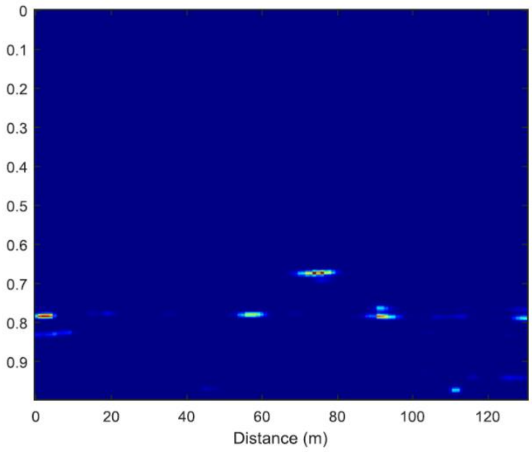


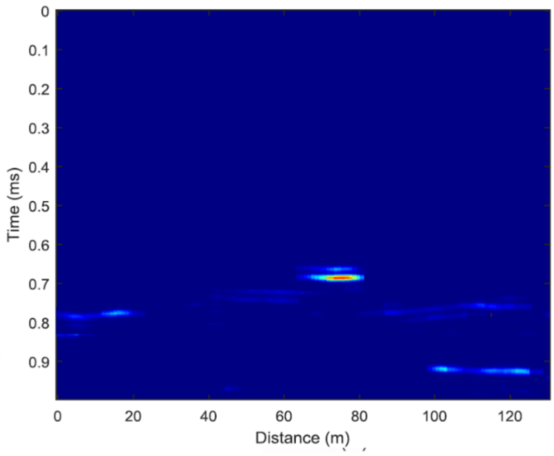
Figure 5. Zero-offset section in which the gas reservoir is represented by the red circle.



(a)



(b)



(c)

Figure 6. a) Gas reservoir anomaly after the first iteration of MC-STFT. b) The section after the second iteration of MC-STFT. c) The result of SSTFT.

3-3. Real model 2

This model is a block in the Dutch sector of the North Sea which is a zero-offset section with 1356 ms of time axis and 23.75 km of distance (Figure 7). The gas reservoir is located approximately in the middle right part of the section which is shown by the red circle. The first and the second iterations of MC-STFT are applied in this section. The first iteration can distinguish the gas reservoir accurately enough (Figure 8a). The remaining anomalies that might be misleading in locating gas reservoirs will considerably vanish by the second iteration of MC_STFT (Figure 8b). Applying the result of SSTFT is shown in Figure 8c, and it succeeded in identifying the gas zone with high resolution.

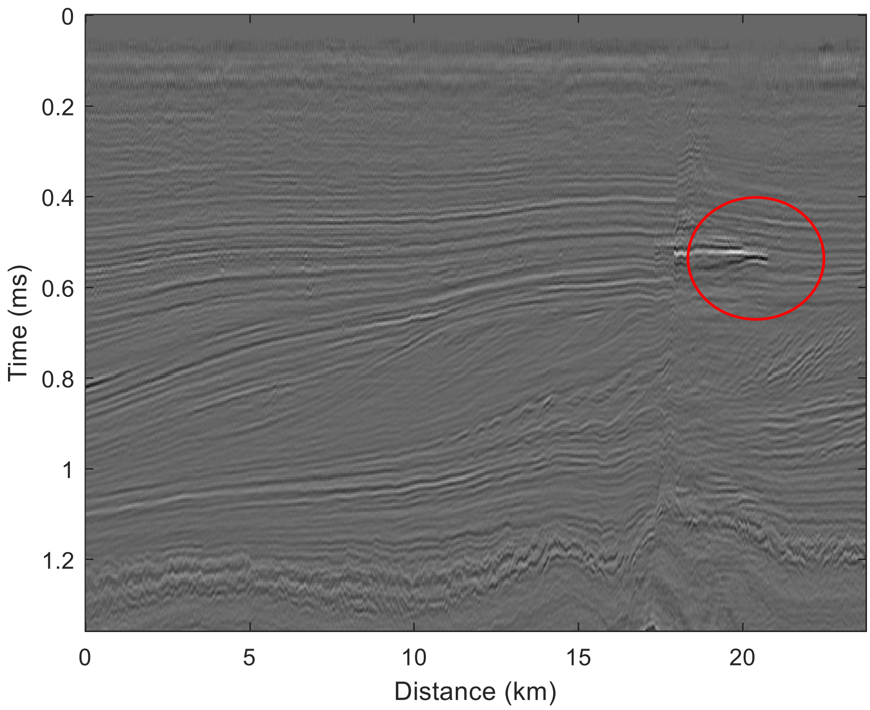
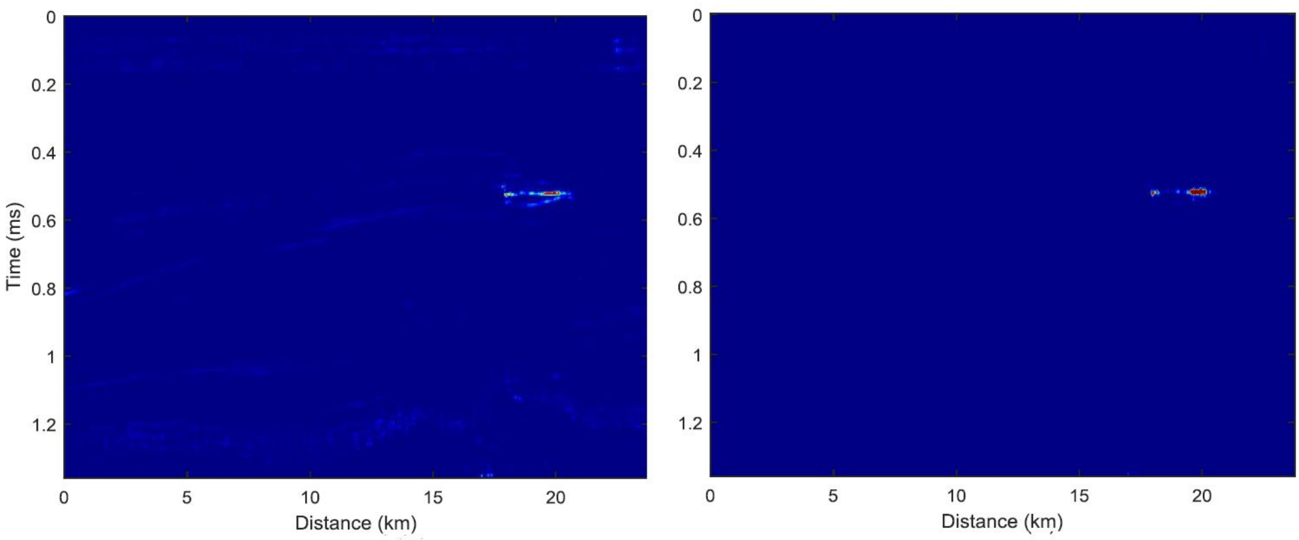
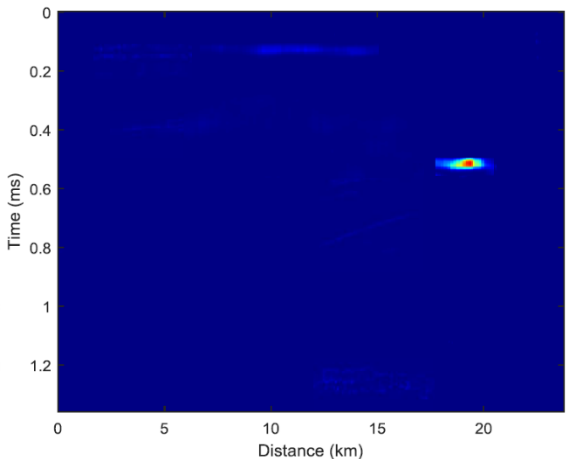


Figure 7. North Sea zero-offset section and the gas target.



(a) (b)



(c)

Figure 8. a) The result of applying first iteration of MC-STFT. b) Second iteration output of MC-STFT. c) The result of SSTFT.

STFT offers a compromise between time and frequency resolution, which is controlled by the window size used during the transformation process. Although STFT provides a constant time-frequency resolution across all frequencies, this can limit its effectiveness in analyzing signals with rapid transient changes because it cannot adapt its resolution to signal characteristics dynamically. This investigation has demonstrated that while STFT offers a straightforward and computationally efficient approach, it is constrained by a fixed time-frequency resolution trade-off, which may not adequately capture the intricate dynamics of signals with rapidly varying frequencies.

4. Conclusion

In this study, we employed STFT in an algorithm to detect gas reservoirs from seismic zero-offset sections. This method adds no complexity to STFT methodology and uses the simple original STFT. In fact, extracting three components of STFT of the zero-offset section and multiplying them is the key that creates this attribute. Two iterations of this algorithm are proposed so that the first one distinguishes the gas reservoir with high accuracy from other events. Consequently, the second iteration increases detection resolution and makes an absolutely precise image. MC-STFT for all of its potential, seismic data are subject to a wide variety of noise-related problems that can and do limit its usefulness. Therefore, in the first stage, pre-processing is needed. In addition, the fixed window size used in STFT can be a significant limitation, as it imposes a trade-off between the time and the frequency resolution. Narrow windows give good time but poor frequency resolution, and vice versa. However, simplicity and efficiency can make a method superior. Results, which tested the proposed algorithm on three real data, also show that the first iteration of MC-STFT can locate gas reservoirs but with some other weak amplitude anomalies. However taking advantage of the second iteration of this method considerably increases the accuracy of gas reservoir location. Also, it should be mentioned that the steps and parameters of the designed algorithm could be optimized in future works to improve its performance for gas reservoir identification. To evaluate the proposed method, SSTFT is also employed and applied to the data, the outputs show its power to localize and identify gas zones. Totally, the final results approved more power and higher resolution of MC-STFT in comparison with SSTFT for gas reservoir detection.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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