FUZZY INFERENCE SYSTEM DESIGN FOR MULTIPLE ATTENUATION WITH QUANTITATIVE VALIDATION CRITERIA USING AUTO CORRELATION ENERGY RATIO (ACER)

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ABSTRACT

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Many methods for multiple attenuation are based on numerous signal properties for years. Each multiple attenuation technique has advantages and disadvantages and is effective for a particular type of multiples. Recently, fuzzy logic has shown wide application in seismic processing and interpretation. A method for multiple attenuation using Radon transform by fuzzy inference system is introduced to run the multiple attenuations step adaptively and automatically. We applied an intelligent adaptive approach based on fuzzy logic to attenuate multiples in each super common midpoint gather automatically and find good results compared to the manual defined mute function in the radon domain. Applying the new method to synthetic and real data has shown the power of the proposed method for multiple attenuations in the area with substantial two-way travel time differences that occurred due to the different water depths. A quantitative validation criterion named Auto Correlation Energy Ratio (ACER) is presented to guarantee that the final result in multiple attenuations using the new proposed approach is correct.

KEY WORDS: multiple attenuation, fuzzy logic, Radon transform, marine data, water depth.

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INTRODUCTION

Multiple attenuation is a critical step in marine seismic data processing. Many methods introduced for this aim are based on either the properties of multiples or the physics of its propagation: periodicity (Peacock et al., 1969), velocity discrimination (Schneider et al., 1965) coherency (Kneib and Bardan, 1994), wavefield extrapolation (Verschuur et al., 1992), move out and dip discrimination (Mayne, 1962; Hampson, 1986). The Radon transform, a powerful tool, has a long history in signal processing. It is an essential tool in seismic data processing with variant modes (Linear, Parabolic, and Hyperbolic).

The seismic processor's role significantly impacts the result of multiple attenuations, especially when a velocity discrimination tool like radon transform is used. Selecting the numerous space in the radon domain is not a deterministic and trivial procedure. The multiple attenuations yield different results when another processor finalizes the task. The neural network (NN), fuzzy classification, and mixed-use (ANFIS) are appropriate tools for removing human uncertainty from seismic data processing and interpretation. These tools help us implement verbal roles in processing and interpretation flows. Using this application decreases the human fault and as a result, the processing and interpretation flow can be automated accordingly.

Many authors introduced the different applications of the NN and fuzzy systems in seismic processing and interpretation flow. Fuzzy logic and the fuzzy variable was primarily raised by Zadeh (1965). Aminzadeh (1991) discussed the expert system in seismic exploration, which uses fuzzy clustering. Finally, Aminzadeh and Wilkinson (2004) reviewed the application of neural networks and fuzzy logic in seismic object detection. They focused on a rule-based neural network to combine seismic attributes and effectively bring data with the interpreter's knowledge to reduce exploration risk.

Coppens (1991) used the rule-based system to determine seismic velocity. He developed the SHIVAAS expert system that aids in interpreting seismic velocity analysis computed as velocity spectra. Finol and D.Jing (2002) used a fuzzy inference system to predict permeability on sedimentary rock using the well log data. Janakiraman and Konno (2002) introduced the method of calculating subsurface geological feathers in the area between boreholes using a fuzzy neural network (FNN), inverted geophysical data (Geo-tomogram), and fuzzy geological knowledge.

Hashemi et al. (2008) presented a new technique based on unsupervised clustering with a fuzzy GK clustering algorithm to detect random seismic noise in pre and post-stack data. They used an adaptive distance norm to discover centers of ellipsoidal clusters and create a partition matrix that defines the soft decision boundaries between seismic events and random noise. Crucelis and Milagrosa (2009) developed an algorithm based on Fuzzy Inference Systems, using fuzzy rules in the form of If – Then to implement first break picking in VSP data automatically. Based on this approach, the error of first break picking has been reduced to 2 (ms) in the presence of noise (e.g., in a low S/N ratio scenario).

Li and Sun (2016) and Sun and Li (2015) used a fuzzy C-means clustering procedure to improve the result of 3D inversion of magnetic data in remnant magnetization and a multi-domain clustering algorithm. They show it can effectively combine statistical petrophysical information into a deterministic inversion. Singh et al. (2018) used FCM clustering to create fuzzy constrained inversion to improve the result of inversion of the resistivity data. He used two fuzzy variables to identify geological units, the mean of resistivity, and L1 and L2 norms to minimize the new fuzzy objective function. Finally, Hadiloo et al. (2018) compare the unsupervised and supervised fuzzy clustering in seismic facies classification in the channel system, extract the seismic facies pattern, and introduce a new GUI software (SeisArt) for this purpose.

Chongjin et al. (2020) used the guided FCM clustering method for joint inversion of the subsurface model's three different physical properties of rocks (gravity, magnetic, and seismic). In this approach, he received steady clustering results with geophysical properties and achieved more reliable results after interpretation.

This paper presents the new fuzzy inference system (FIS) based on the knowledge of seismic processors, attributes in the radon domain, and theoretical approaches to create a fuzzy system to attenuate the multiples automatically. First, some note about the fuzzy system and fuzzy logic is introduced, then a fuzzy jointing system and multiple attenuation methods is targeted. Finally, a simple fuzzy system for multiple attenuations is constructed, and discussion and conclusions are made. The main goal is the automation of Radon transform with a quantitative measure in an adaptive CDP per CDP (Super CDP per Super CDP) manner.

FUZZY LOGIC AND FUZZY INFERENCE SYSTEM

The concept of fuzzy variables against crisp variables is the most critical achievement (Zadeh, 1965). Fuzzy logic is a platform to use linguistic variable and knowledge-based information as mathematical operations. Fuzzy logic developed in a wide range of science for control and operating systems. The application of fuzzy logic and the fuzzy system has significant advantages and added value, especially in the interpretation of data. For example, there are many variables in seismic specialists dependent on the point of view of the processor/interpreter, and manual parameter change by the user is needed. Also, fuzzy logic is used as a tool in processing sequences in seismic data processing, like first break picking by Gao (2019), automation of seismic processing (Hashemi, 2018), and random and coherent noise attenuation (Hajian, 2016). Here, it is intended to use fuzzy logic to automate multiple attenuation by radon transform approach, which is one of the key steps in marine seismic processing.

MULTIPLE ATTENUATION IN FUZZY LOGIC TERMINOLOGY

FIS Generation Approach

The task in this section is to link fuzzy and multiple attenuation methods. There are some suggested approaches to connect fuzzy methods to multiple attenuation methods:

1. Choosing the best method for multiple attenuation in the area with different types of multiple and diverse geology by fuzzy inference system (FIS). Multiple attenuation methods usually use their properties for the suppression step. Different multiples types are created in the area with diverse geology along a 2D seismic line or in 3D seismic data. So applying only one method for multiple attenuation while other sources are possible is inefficient. For this reason, it is necessary to use more than one method to suppress numerous energy of a seismic CDP gather. To accomplish this job, we cannot check all the CDP gathers. It is also impossible to get through different types of multiple attenuation techniques and select the best method (and best parametrization) to lose primary energy. So, a tool with an adaptive intelligent approach is needed to automatically do this task and suggest the best multiple attenuation method CDP per CDP. Fuzzy logic and fuzzy system are the proper applications due to their definitions in incorporating membership functions, verbal rules, and/or/not rule changes possibility and knowledge combination of input attributes. It is necessary to list the limitation of different types of multiple attenuation methods to have a guideline for choosing the proper way depending on the multiple types and geology structures. These limitations and extra information, such as variations of water depth and autocorrelation for all traces in each shot gather or CDP gather can be initial information to build FIS to choose multiple attenuation methods for each shot or CDP gather.

Table 1. Limitation of different multiple attenuation methods.

	Method	Limitations
	Radon Transform	Depending on Multiple-Primary Mute Function Selection by Processor
	SRME	Limitation of Variable Water Depth
	Predictive deconvolution, Radon Transform	Limitation in Area with Complex Geological Structures (Sheng et al., 2014)
	Radon Transform	Limitation on Extending the Muting Function for All Data in Area With Complex Geology and Variable Water Depth
	Transform, Radon Transform F-K	Limitation in Near Offset (Yuza et al., 2020; Yilmaz, 1989)
	SRME	Requires Dense Data and Regular Survey Geometry
	Predictive Deconvolution	Limitation in Far Offset (deep water) (Xiao et al.. 2003)

2. Some methods of multiple attenuation need a set of initial parameters or choosing a mute area by a processor like demultiple using Radon transform and F-K transform. The initial parameter setting and muting are significant challenges in these methods. These will be more severe when variable water depth and complex geology are subjected to creating different multiples. The presenceof multiple types in the complex area initiates the idea of using different muting in the Radon and F-K domain. In the conventional method, some information comes from the nature of multiple and primary events in the transform domain, t-x domain (CDP gather or shot gather), and their physical property. This information can be used in FIS as a knowledge-based FIS to increase the targeted method's efficiency. Based on the advantage and disadvantages of multiple attenuation methods, the seismic processor transforms it into the fuzzy if-then rules.

In addition to processor knowledge and experience-based information, some additional rules in an attribute can be extracted from seismic data or attributes in transform domain like frequency attributes, texture attributes, geometry attributes, statistical attributes, and so on that help generate better FIS.

Table 2. Fuzzy if-then rules from the seismic processor's knowledge and experience.

If	Then
Increases in water depth (the curvature of the event increases)	The event probably is multiple
The intercept time of an event is lower than two times of the seafloor	The multiple is not water bottom multiple
The events with different intercept times have the same curvature	Probably the events with the higher intercept times are multiple of the primary events
The input events in the radon transform are hyperbolic, parabolic, or linear	The events map to a point in the corresponding radon transform
In the SRME method, if the water is shallow	The accuracy of the method in attenuation of the bottom water multiples is reduced
If the type of multiples are short period	The best method for multiple attenuation is predictive deconvolution
If the data contains far offset values	predictive deconvolution is not successful
In the absence of variable speed in input data	F-K and Radon methods are problematic

Clustering Approach

Commonly, there are two types of FIS generation methods (Guillaume, 2001). In the first method, theoretical information separates the target domain into a model-based FIS generation class. These FIS include fuzzy rules made from expert knowledge, and they are called fuzzy expert systems or fuzzy controllers, depending on their ultimate use. It also facts out the limitations of human information, particularly the difficulties in formalizing relations in composite processes. Moreover, this type of FIS suggests a high semantic level and a good generalization capability. Another class of FIS generation is based on automatic learning from data, generally indicated as data-based FIS generation, to automatically separate the target domain to an unknown cluster and create an intelligent FIS for a specified aim.

In this study, both steps for rule generation are used in the final fuzzy system. In the first step, using model-based FIS and a theoretical approach, the radon domain can be separated into different classes containing multiple areas, primary area, and noises in the radon domain. We used class multiple as an output of this approach. Secondly, we used the output of the model-based fuzzy system as output for fuzzy data-based system. Rule generation in this type of FIS will be done using automatic learning, depending on the input property. In this way, fuzzy clustering using FCM (Bezdek et al. 2003) is used to cluster input and output data to different classes.

The critical point in this procedure is the number of clusters in input and output data directly affecting the final result and class separation. Commonly, the number of classes must be more than those represented on data in the fuzzy system and can be separated into different categories. There are three main classes in our problem: multiple, primary, and noise. So, we need to select a number of clusters (classes) in input data more than 3.

Now, some essential questions are coming next below.

1) How to choose the number of classes? And what are the reasons?
2) What is the correct or best membership function for input and output?
3) Are there redundant rules (clusters) in the initial clustering?
4) Can the final FIS extracted from one or more CDPs be extended to other CDPs or seismic lines?

The answers lead us to this final clustering system identification:

1. The number of classes in initial clustering depends on the number of classes in the data. It must be selected more than it all of the properties in data extracted in different classes to optimize the final FIS using its rules and link these rules with those extracted using expert knowledge.

2. The type of membership function areas varied from one CDP to the next. This affects the selection of membership functions. Therefore, its property must be extracted and optimized for each CDP and is varied to the nearby CDP. This procedure uses energy distribution in the radon domain and extra information about the target CDP like water depth. As a result, we propose using a Gaussian or Π-shaped membership function for all axes in input and output variables.

3. The redundant rule in initial clustering is trivial. The number of rules is much more than the number of clusters in the data, but the main question is how to find the best number for the clusters for initial clustering? Presenting a general method for accomplishing this action is not feasible, but we can include the sense of seismic processor and type of energy distribution in the radon domain. These can help the seismic processor select the best number for initial clustering. The process of the initial clustering may be made two or three times to find the best number of clusters. By the way, after selecting the number of clusters, it is necessary to check different rules and solve the problem of the redundant rule. So, the selection of the cluster numbers is highly affected by the rule optimization procedure done after initial clustering. Removing the redundant rules can be influenced to obtain a better FIS with the best performance in multiple attenuations.

4. The generalization of the extracted FIS on the part of the data shall be used for all of the data along with of seismic line or seismic area. In addition, some extra and detailed information about the study area shall be accessed, and the geological structure of the near-surface will be targeted. Finally, a deep system to prepare the out FIS is found, and the processor can import information in the middle of processing if needed.

Implementation of multiple Attenuation using FIS

For implementing multiple attenuations in the radon domain using fuzzy in practice, the real data from the Gulf of Mexico is used as a sample to achieve the best and most efficient way to execute fuzzy tools on real data. In the first step, the parabolic Radon transform perform on NMO corrected gather, and the input data for fuzzy clustering is ready. The input data in this approach for multiple attenuation is the Radon transform of NMO corrected gather. We need to add some extra information to input data for clustering with enough accuracy. This additional information can be some attributes in the Radon domain, such as geometry attribute, texture attribute, frequency attribute, statistical attribute, etc. Each attribute category is sensitive to one feature type (orientation, frequency behavior, statistical behavior of target data) in the target domain. Due to the inherent difference between original data in the offset domain and transform data in the radon domain, many attributes mentioned above are not helpful for the specified purpose. So, a wide range of characteristics in the radon domain is checked to find the efficient attribute class number for clustering the radon domain to perform the task correctly. The texture and edge attributes (Zarei and Hashemi, 2019) are good candidates for involvement in fuzzy clustering. Also, we used water depth as a tool to define a label in Radon transform and apply this labeling to input data for fuzzy clustering.

Some arbitrary values are primarily tested to find the optimum number of clusters in the radon domain. Depending on the class separation for each, the number of classes as ten yields the best results for the final clustering procedure. Since the 3 class of data is initially assumed in the radon domain (primary area, multiple area, and random noise), logically, the optimum number of clusters for fuzzy clustering is targeted as three, but this is not the best choice in every situation. This is because the separation of these three classes is not feasible due to the high values of the class overlap.

Figs. 1 and 2 show the extracted rules from data using FCM clustering with 5 and 10 clusters. As shown in these figures, the class separation shows a reasonable rising rate with increasing the cluster number, although the redundant rules are growing. The problem of redundant rules can be handled by merging or removing these rules. The direct result of this discussion is "with an increasing number of clusters to 20 or more, better discrimination of classes is reached.". This statement shall be considered "true" or "false." This is "true" because with an increase of cluster numbers, class discrimination increases, and it is false because instantaneously, the redundant rules and runtime of multiple and primary separations are increased. It is necessary to care for the optimum number of clusters because the multiple in each data varies depending on the property of multiple created on the surveying area.

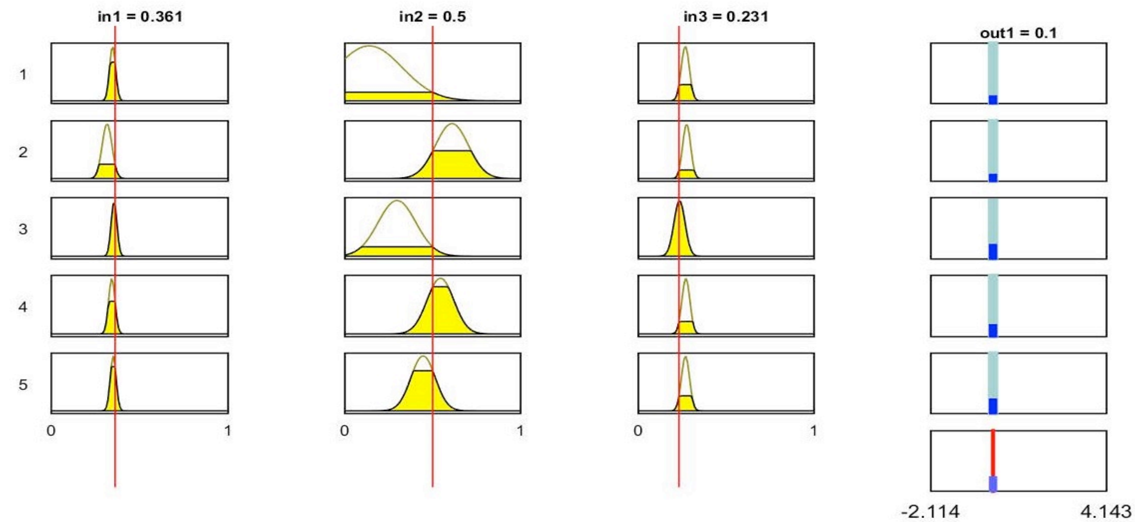

Fig. 1. The generated rules with five clusters using FCM clustering.

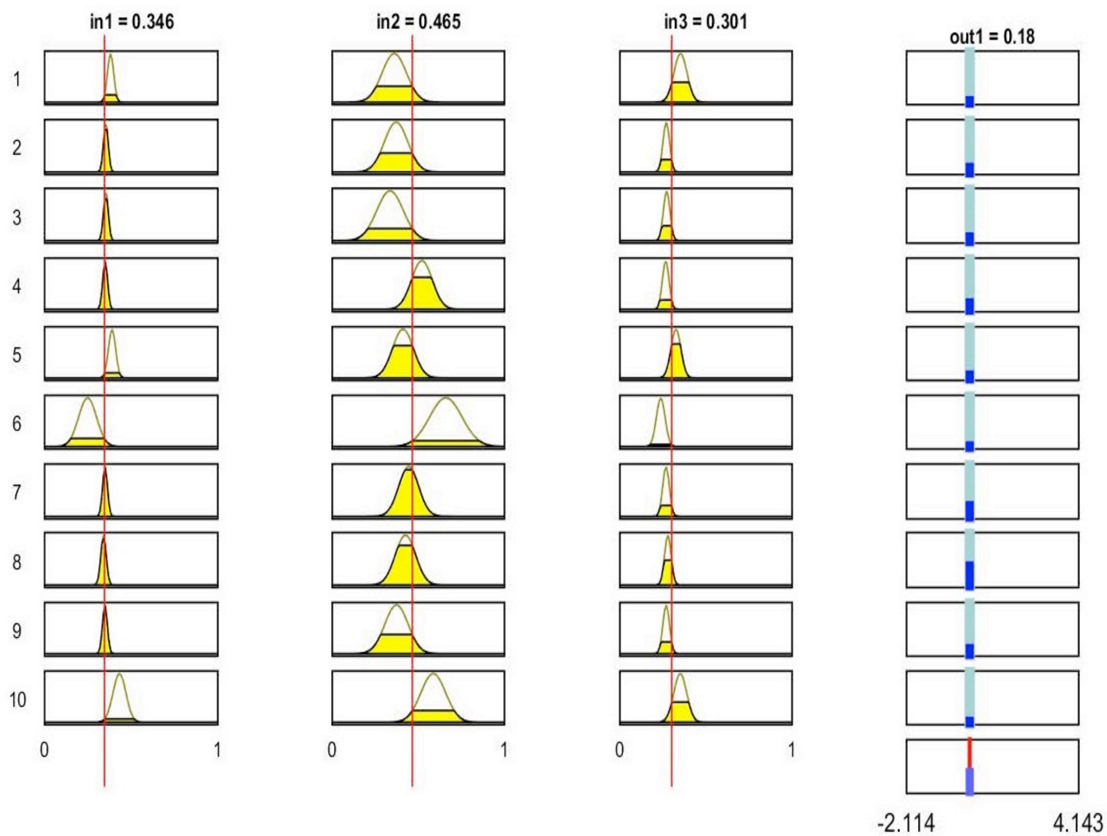

Fig. 2. The generated rules with ten clusters using FCM clustering.

As the output of this step, we achieved the appropriate FIS for multiple attenuation. The next step is the automation of multiple attenuation, which is done using the Adaptive Neuro/Network-based Fuzzy Inference System (ANFIS). The multiple attenuation is automatically done using this tool, and the mute function is adaptively identified in each CDP. The output of ANFIS is a radon panel in which the multiple area is in the region with the sharpest energy of the radon domain. So, with the amplitude thresholding, the multiple area and mute function are created, and this mute function is applied to the original radon panel.

Fig. 3 shows the flowchart of adaptive multiple attenuation using parabolic Radon transform with variable mute function.

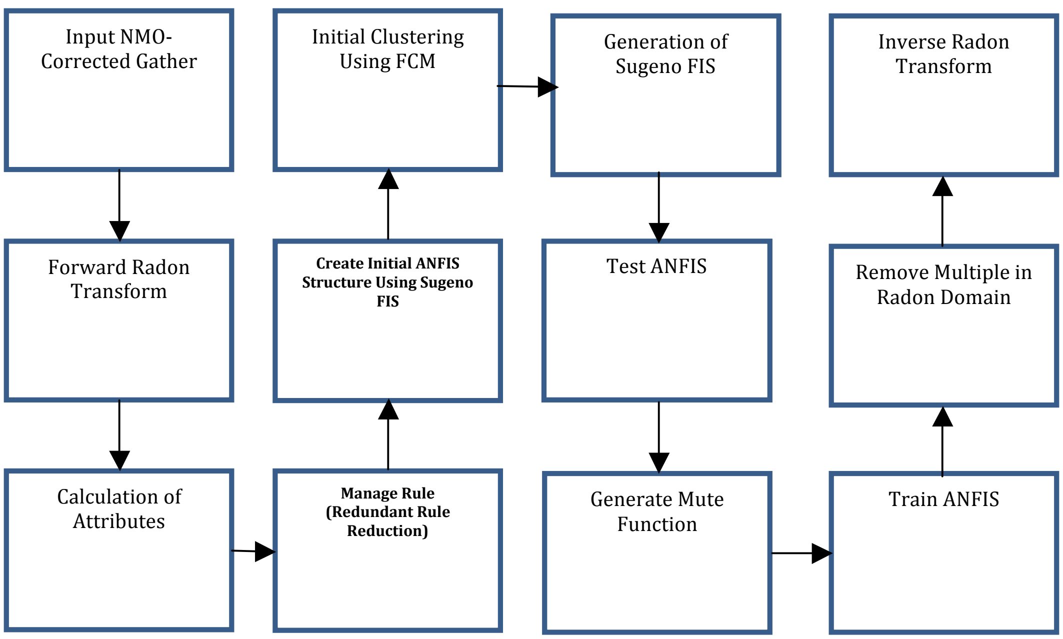

Fig. 3. Flowchart of Multiple Attenuation using ANFIS.

Application to Synthetic Data

A synthetic CMP gather is generated containing five primary and two multiple events. The model features are identified in Table 1. The sample rate is 2 (ms), and the offset variety is 12.5 (m) to 3025 (m) with an interval of 12.5 (m). A zero-phased Ricker wavelet with a central frequency 20 (Hz) is used to generate a seismogram. The S/N ratio for generating synthetic data set is level five because it can be tested methodology in the presence of noise. The data, its corresponding NMO corrected gather (of input CMP gathers), and its parabolic radon transform is shown in Fig. 4.

Table 3. The properties of the synthetic model (Zarei and Hashemi, 2021).

Event No.	TWT (ms)	Velocity (m/s)
1	500	1500
2	800	1800
3	1300	2200
4	1800	2500
5	2200	2800

The result of applying multiple attenuation by the fuzzy system is shown in Fig. 5. The input parameter for this synthetic data is prepared and imported into the ANFIS structure. As shown in Fig. 5(b), multiple areas are highlighted as the radon domain's highest energy part, so the mute function is extracted using amplitude thresholding [Fig. 5 (c)]. Finally, the multiple events reconstructions perform using the mute function [Fig. 5(d)] and then subtracted from NMO gather [Fig. 5(e)].

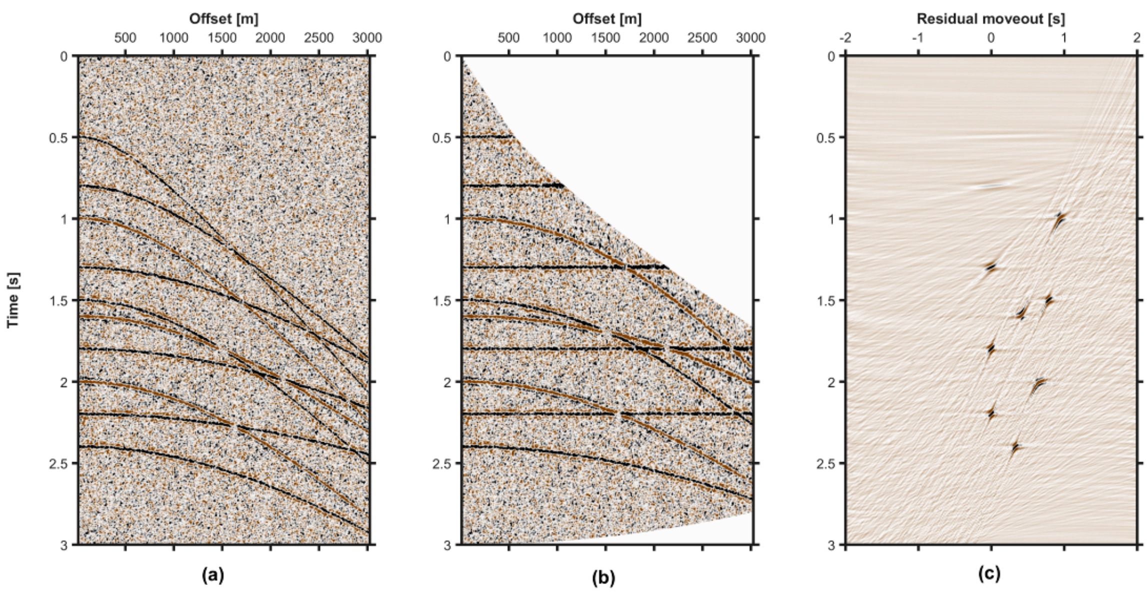

Fig. 4. Synthetic data (a), NMO Gather (b) and Radon Transform of NMO gather (c).

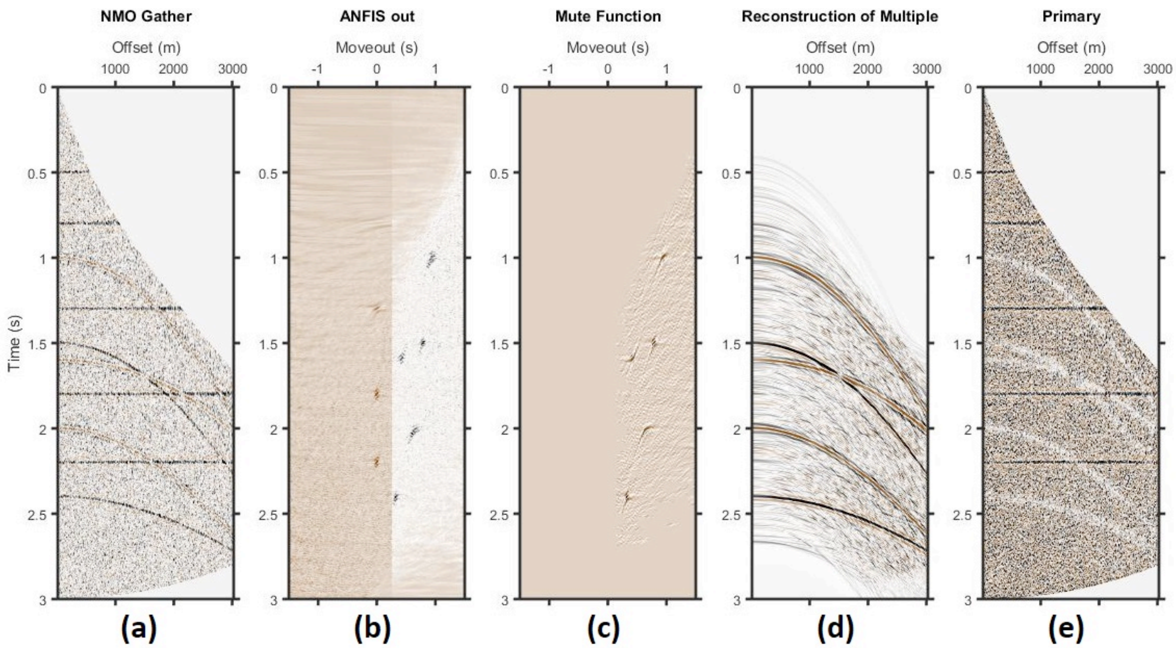

Fig. 5. (a) NMO Gather. (b) ANFIS output (a). (c) Mute function created by ANFIS. (d) Reconstruction of multiple from panel (c). (e) Primary event [panel (a)-panel (d)].

Application to Real Data

To confirm the ability of the presented method in the different areas with different types of multiple, we used two data sets from the Gulf of Mexico and the Oman Sea. Fig. 6 shows the results of multiple attenuation for the data set from the Gulf of Mexico. Multiple areas are definitely modeled using the mute function created by ANFIS tools. The mute function completely covers the considerable area without any deviation and distortion. Also, some places in the radon panel included multiple locations (shallow time, high moveout) that may contain some signal energy in this method removed from the mute function.

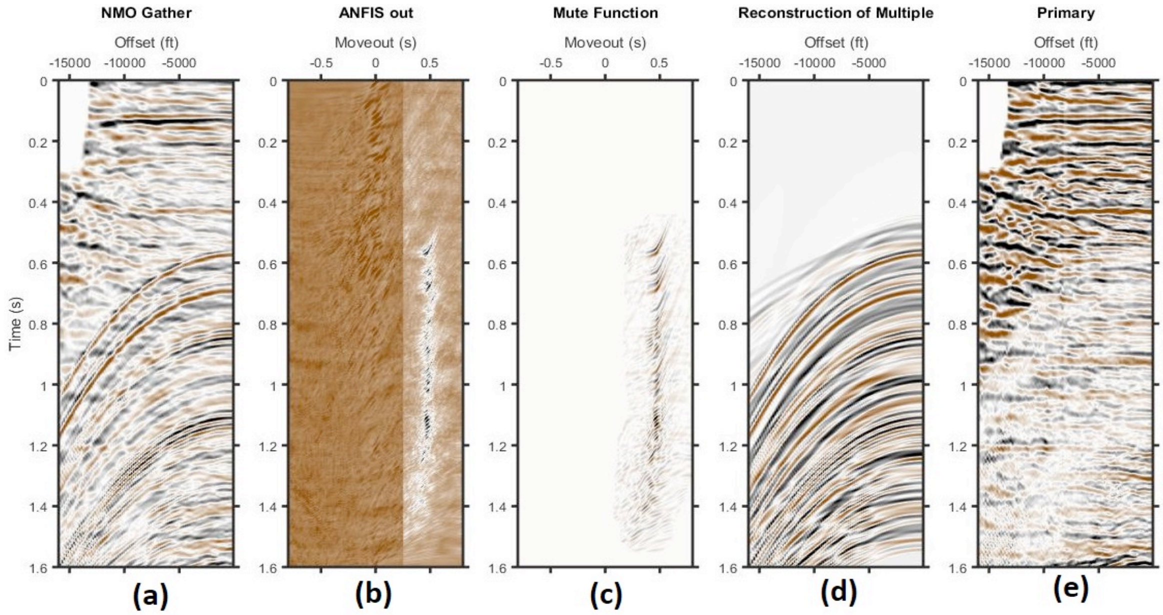

Fig. 6. (a) NMO Gather (Gulf of Mexico). (b) ANFIS output (a). (c) Mute function created by ANFIS. (d) Reconstruction of multiple from panel (c). (e) Primary event [panel (a)-panel (d)].

Another data set is used to show the application of the method on a marine data set from the Oman Sea. This data set is a 2D line that was recorded in 2000. The geology of this zone near the shore is similar to a typical vertical transverse isotropic (VTI) media in a shallow depth, and the section also encloses deep water effects far from the seashore, bottom simulating reflector (BSR), and other events are visible as well. The sea depth differs from zero to more than 600 meters beside a seismic line perpendicular to the shore, generating different multiples in seismic data (ranging from a short period to a long period). So, multiple removals of seismic data in this area are one major step in the processing sequence, and the big challenges are a change of multiple types and the existence of anisotropy, especially in the lower depths. BSR follows the seafloor topography, and it is highly possible to remove data as multiple. Because the different types of multiple exist in data, the energy distribution in the radon domain is varied in the seismic line according to the seafloor depth, so other mute functions must be applied for efficient multiple attenuation. Fig. 7 shows the stack section that we used to test the new method. As seen in this figure, different multiples exist in this dataset, and water levels extremely change in the seismic line.

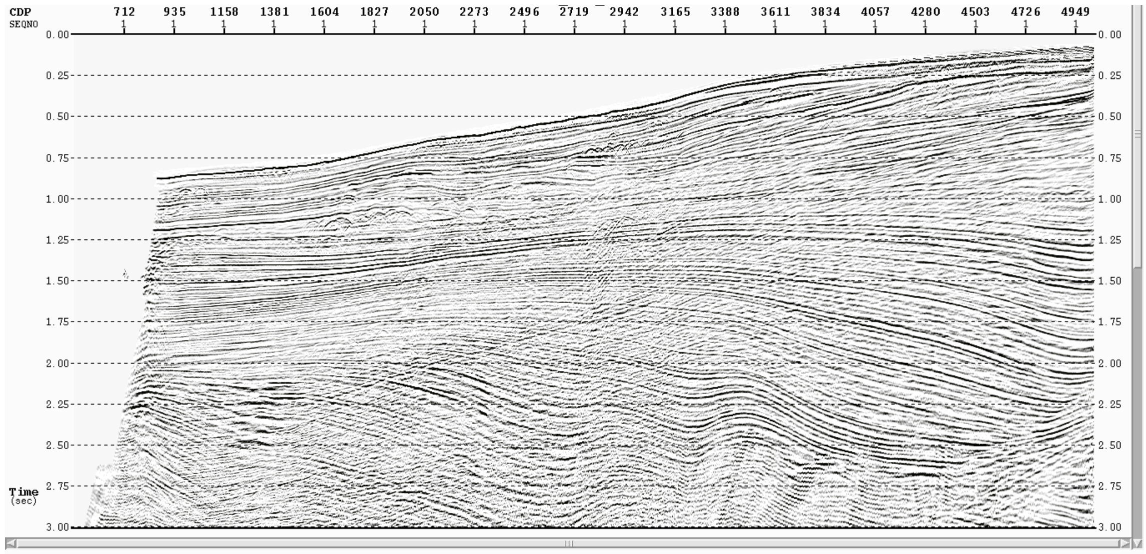

Fig. 7. A Stack Section of the marine seismic data from the Oman Sea.

In the conventional method for multiple attenuation, one mute function eliminates multiple in all CDP vintages. However, this may affect signal energy because it is hard to define one mute function to eliminate all multiples in the whole seismic line.

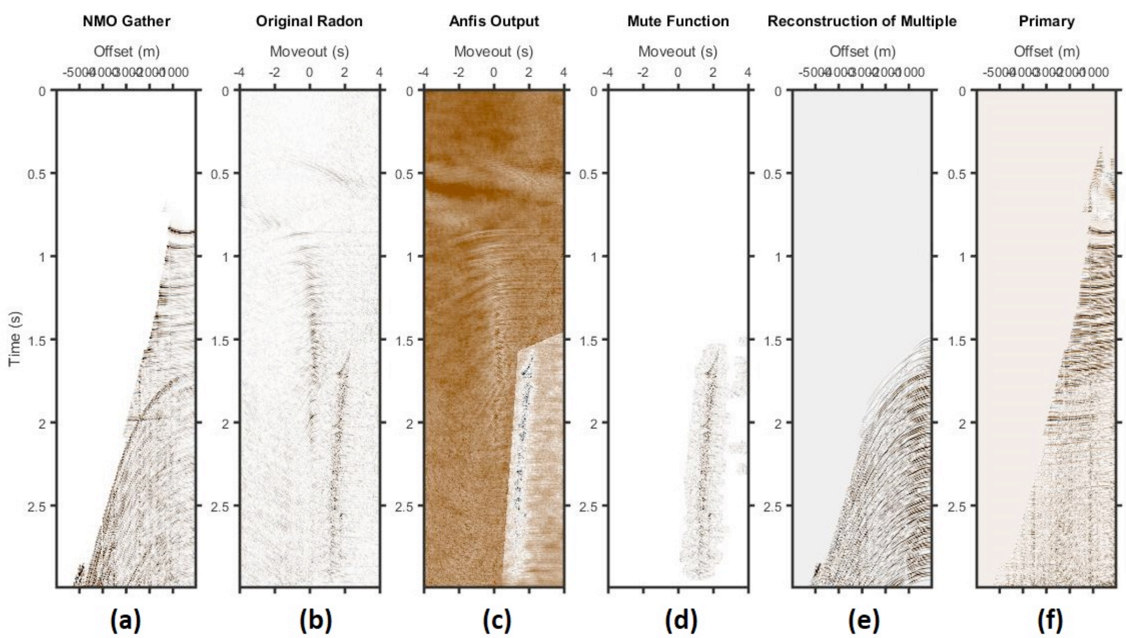

Fig. 8. (a) NMO Gather (Oman Sea, CDP=1000). (b) Parabolic Radon of panel (a). (c) Output of FIS. (d) Mute function created by ANFIS. (e) Reconstruction of multiple from panel (d). (f) Primary event [panel (a) - panel (e)].

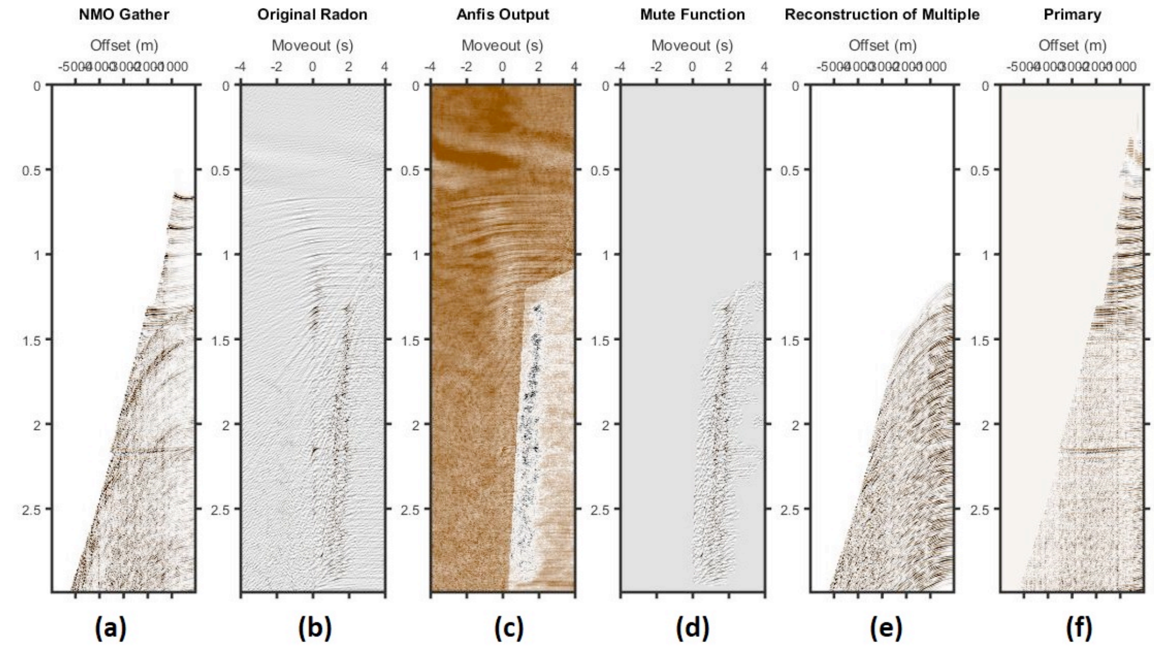

Fig. 9. (a) NMO Gather (Oman Sea, CDP=2000). (b) Parabolic Radon of panel (a). (c) Output of FIS. (d) Mute function created by ANFIS. (e) Reconstruction of multiple from panel (d). (f) Primary event [panel (a)-panel (e)].

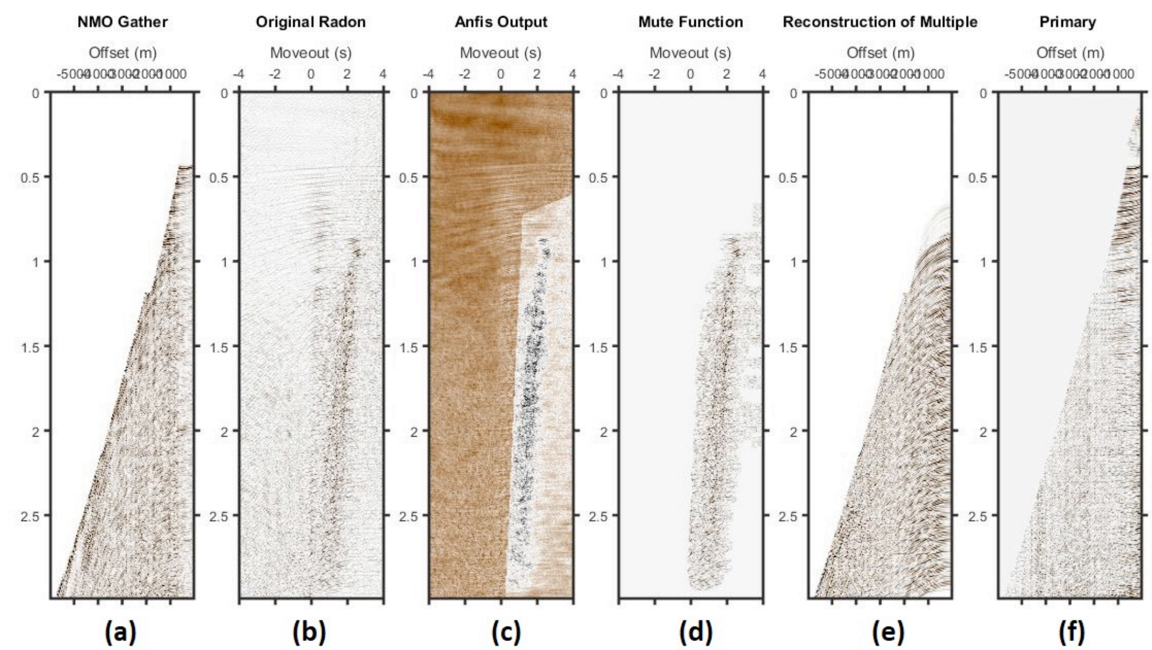

Fig. 10. (a) NMO Gather (Oman Sea, CDP = 3000). (b) Parabolic Radon of panel (a). (c) Output of FIS. (d) Mute function created by ANFIS. (e) Reconstruction of multiple from panel (d). (f) Primary event [panel (a)-panel (e)].

Figs. 8 to 10 show that multiple elimination is done for different CDP locations with changing seafloor depths. As seen in these figures, by decreasing water level, energy distribution then area of multiple in radon domain changes. Therefore, removing multiple energy from the radon domain with the one mute function is impossible. Thus, in the new method using FIS and with the adoption of FIS by a neural network (ANFIS) mute function is individually defined in each CDP against the conventional method that used one mute function.

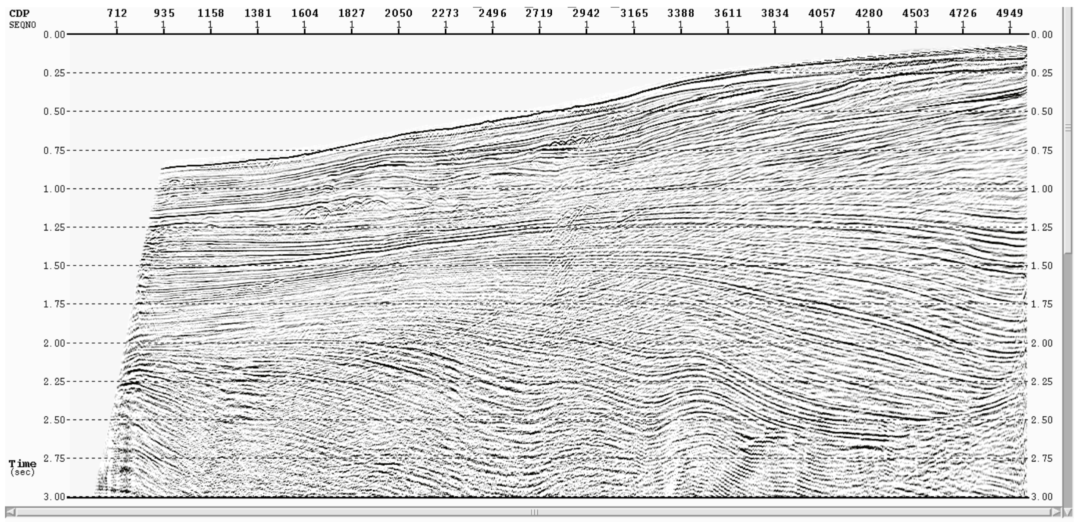

Fig. 11. Multiple attenuation using parabolic Radon with a single mute.

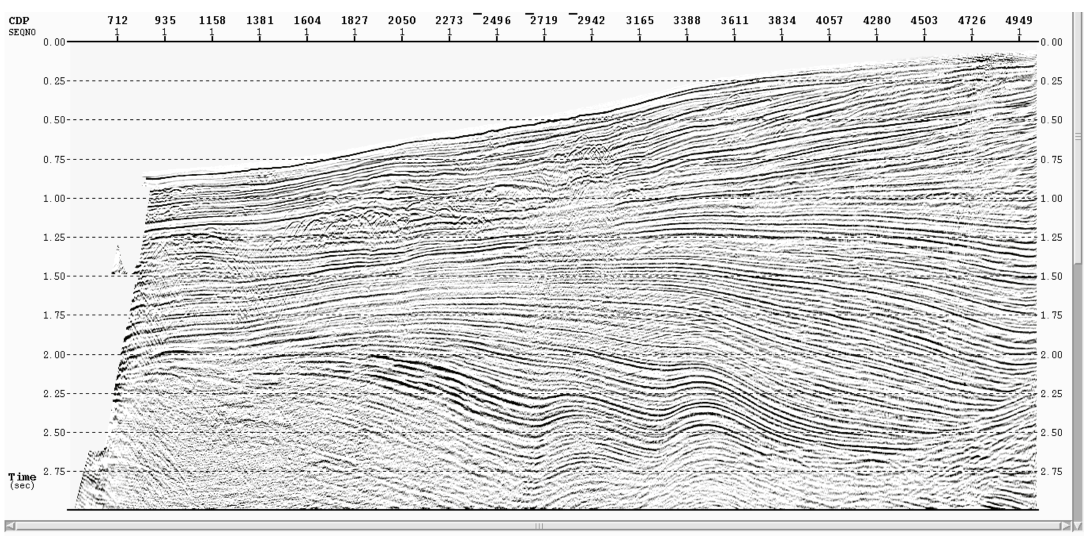

Fig. 12. Multiple attenuation using ANFIS (variable mute).

Figs. 11 and 12 show the result of multiple attenuation using the conventional mute function definition, and the presented method defines the mute function automatically and adaptively. In these figures, some part of multiple energy remains in the stack section with a single mute function, while there is no multiple energy in the stack section with a variable mute function.

To show the final result of multiple attenuation and compare between constant mute and variable mute function in Radon demultiplex, we magnified a small portion of the stack section in

Fig. 13., as seen in this figure, the continental dip, constant mute is failed, and variable mute removed almost all parts of the multiple signals.

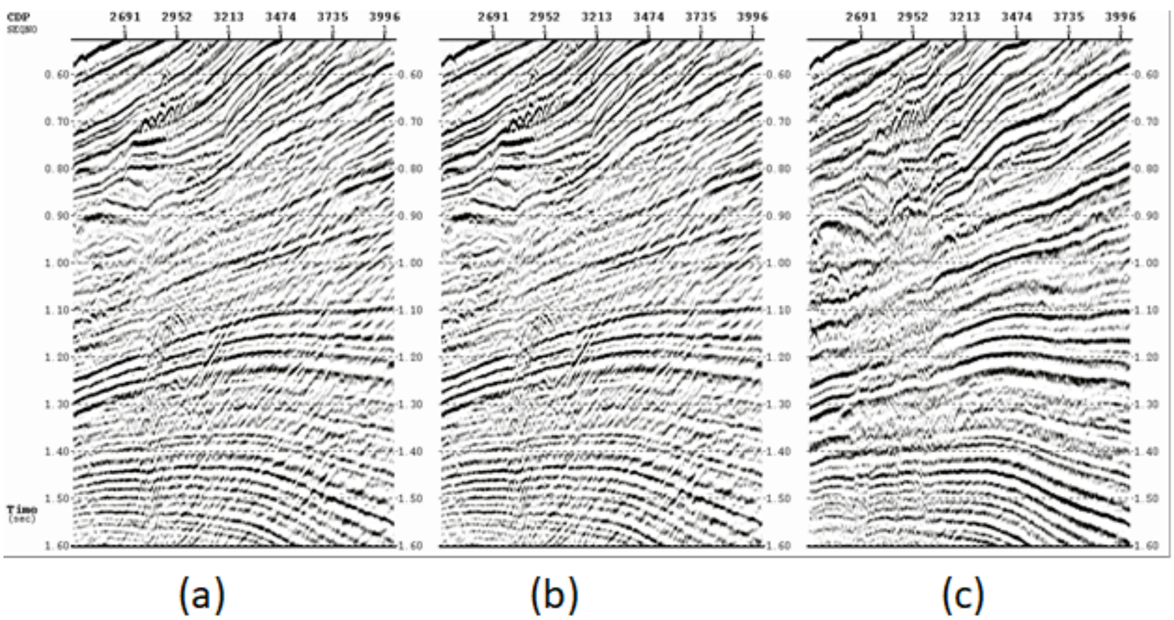

Fig. 13. a) Stack section before multiple attenuation, b) stack section after multiple attenuation using constant mute, c) stack section after multiple attenuation using variable mute.

Quantitative Validation using AutoCorrelation Energy Ratio (ACER)

The new method for multiple attenuation needs a tool to compare its result with different methods used for multiple attenuation. Typically, the qualitative comparison is made using autocorrelation of the stacked section before and after multiple attenuation. We present a quantitative tool based on autocorrelation energy ratio (ACER) as a powerful tool to certify the introduced method can handle multiple attenuation in the presence of complex structures and variable water depth. The autocorrelation section for real data from Oman Sea before and after multiple attenuation using conventional parabolic Radon transform with single mute function and new method that used variable mute function in the whole line shown in Figs. 14 to 16.

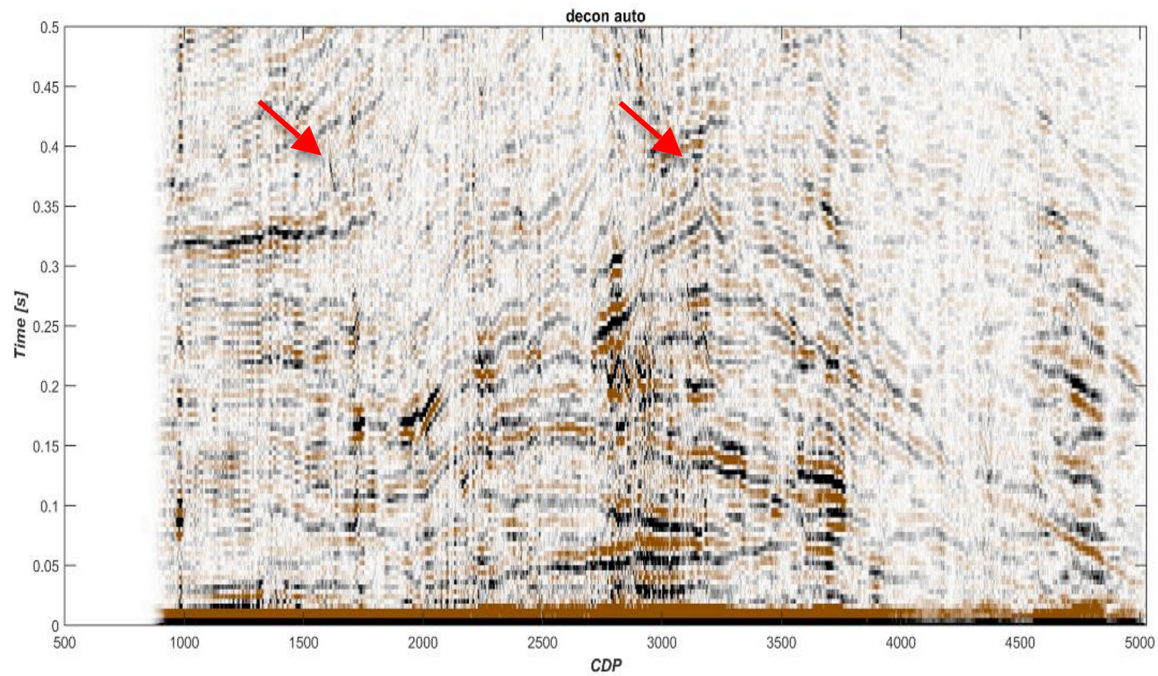

Fig. 14. Autocorrelation section before multiple attenuation, the red arrow shows multiple locations in the autocorrelation section.

Multiple events were highlighted using the red arrow (Fig. 14) and green arrow (Fig. 15). Comparing the time of arrow in the autocorrelation section (Figs. 14 and 15), a partial energy reduction appears in the pick associated with the green arrow because of multiple attenuation using conventional Radon transform with a single mute function almost in the left panel of autocorrelation section. This autocorrelation energy pick, highlighted with the green arrow, shows that the single mute function can't handle multiple attenuation in areas with complex structures and considerable differences in water depth.

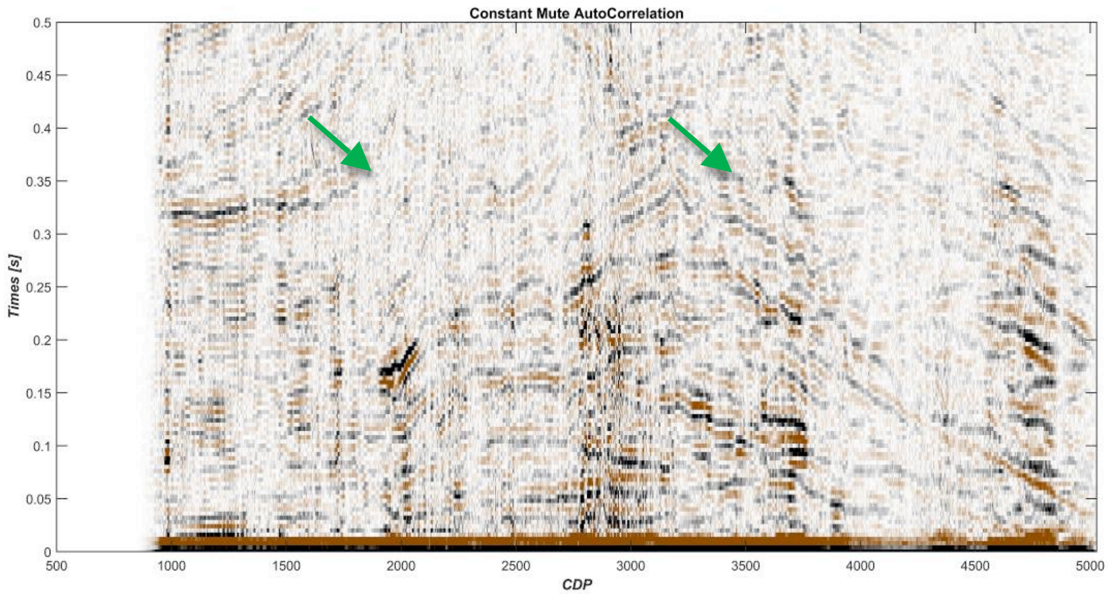

Fig. 15. The green arrow shows multiple locations in the autocorrelation section after multiple attenuation using conventional parabolic Radon transform.

As seen in Figs. 14 and 16, multiples are clearly present in the autocorrelation section. Still, after the used variable mute function that was created using the fuzzy system, almost all of the multiples disappear from the autocorrelation section except a small part of the line in the CDP number 500-950. This is because this portion of the stack section has low fold coverage.

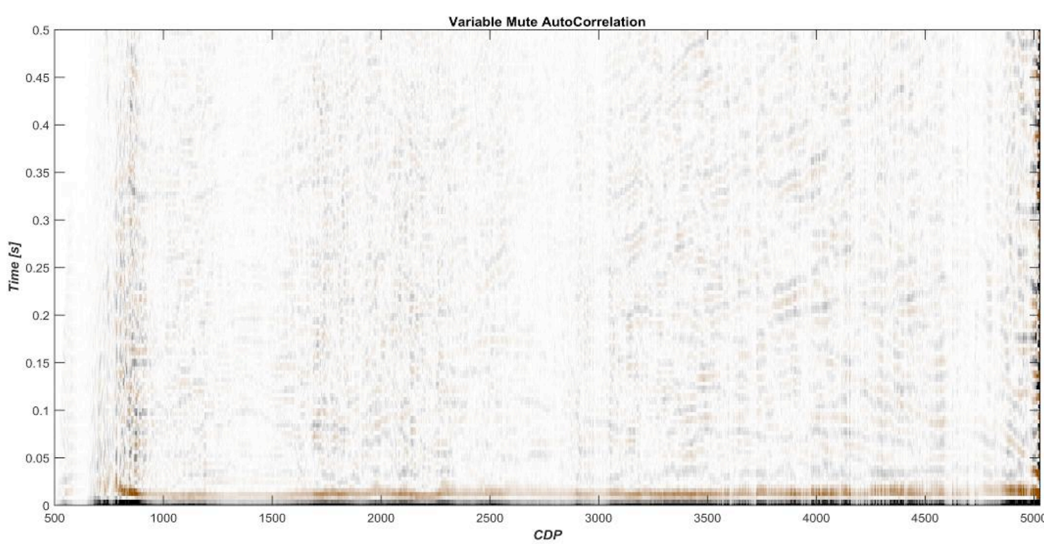

Fig. 16. Autocorrelation section after multiple attenuation new method with variable mute function.

We used the energy ratio as a quantitative measure to show the new method's performance in multiple decreases. Initially, the auto-energy energy was calculated for autocorrelation between 0 and 100 milliseconds for the three parts of the autoimmune (Figs. 14-16). The autocorrelation energy was estimated between 100 and 500 milliseconds in the second stage (Fig. 17).

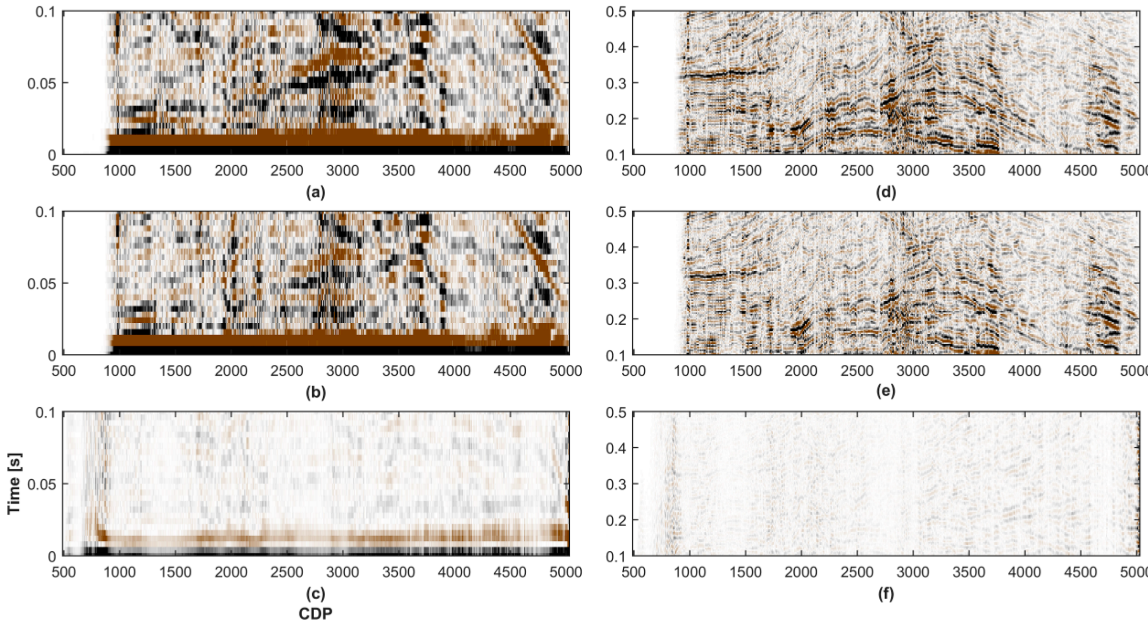

Fig. 17. Autocorrelation energy between 0-100 & 100-500 ms for three autocorrelation section Figs. 14-16.

As we expect, this energy ratio directly depends on the success of multiple attenuation methods. If multiples are removed using the current techniques, this is high, and if multiples are present in the autocorrelation section, this ratio is low.

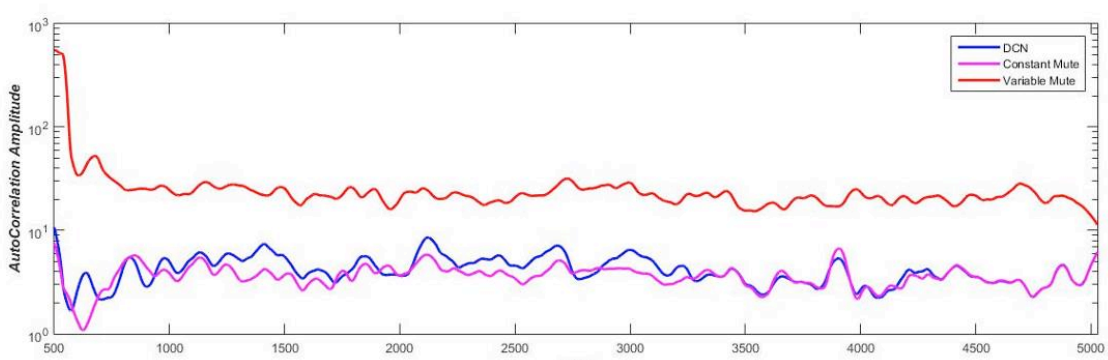

Fig. 18. ACER calculation for Fig.17.

Figs. 17-a, 17-b, and 17-c show the energy between 0-100 ms of the autocorrelation section and Figs. 17-d, 17-e and 17-f, show the energy between 100-500 ms of the autocorrelation section of Figs. 14-16. The result of ACER calculation for three autocorrelation is shown in Fig. 18. ACER ratio for multiple attenuation with the variable mute compared to conventional parabolic Radon transform with single mute function and autocorrelation section before multiple attenuation is considerable. This shows the acceptable performance of the presented method in multiple attenuation in the presence of complex structures and variable water depth.

CONCLUSION

In this paper, the benefits of fuzzy logic and FIS are reviewed, and it has been shown how to use this powerful tool to attenuate multiples from 2D seismic data without the handy piking of the mute function. Also, we created a FIS to automate the multiple attenuation in the radon domain using the original Radon and some attributes in the radon domain. All of the parameters for performing multiple attenuation are adaptively discussed, and how to set the optimum parameters for FIS is explained. The limitation of the conventional multiple attenuation method is listed, and it is used to create fuzzy if-then roles for FIS generation. Applying the introduced process to synthetic and real data shows the advantage of fuzzy radon transform.

The new method results show that the classical radon demultiple in the area with variable water depth (subduction zone and continental dip) is failed, and multiple energy will not be attenuated by variable mute. The flexibility of the mute function can easily remove most part (near to all) of multiple signals. Also, the ACER ratio as a quantitative criterion showed the good performance of the new method.

A significant added value of the introduced method is that the attenuation of multiples is done entirely automatically without manual intervention, and hence it is independent of the user. Another advantage is hidden in the result of multiple attenuation, it still remains constant by changing the user. The progress of multiple attenuation can be made adaptively and CDP per CDP. Moreover, in future studies, it is feasible to distribute FIS application to decide to discover which method yields the best result for applying to each data set using preliminary knowledge and database information.

The idea of separating primaries and multiples in case of overlap is achieved by the variable adaptive mute function introduced in this paper. Generating a radon transform with a variable and adaptive mute function working CDP by CDP can significantly enhance the effectiveness of seismic multiple attenuation, allowing for more accurate and reliable imaging of subsurface structures and features. This approach is particularly valuable for complex geological settings and scenarios where overlap energy is a significant source of interference.

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