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Seismic Fault Preserving Diffusion

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13 **Abstract**—This paper focuses on the denoising and enhancing of 3-D reflection seismic data. We propose
14 a pre-processing step based on a non linear diffusion filtering leading to a better detection of seismic faults.
15 The non linear diffusion approaches are based on the definition of a partial differential equation that allows
16 us to simplify the images without blurring relevant details or discontinuities. Computing the structure
17 tensor which provides information on the local orientation of the geological layers, we propose to drive the
18 diffusion along these layers using a new approach called SFPD (Seismic Fault Preserving Diffusion). In
19 SFPD, the eigenvalues of the tensor are fixed according to a confidence measure that takes into account the
20 regularity of the local seismic structure. Results on both synthesized and real 3-D blocks show the
21 efficiency of the proposed approach.

22 **Keywords**—3-D filtering, anisotropic diffusion, confidence measure, seismic data, structure tensor.

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23 **1. Introduction**

24 The acquisition and processing of reflection seismic data result in a 3D seismic block of acoustic
25 impedance interfaces. The interpretation of these data represents a delicate task. Geological patterns are
26 often difficult to recognize for the expert.

27 This interpretation of seismic blocks mainly consists in reflector picking (i.e. identifying and recording the
28 position of specific reflection events) and fault plane locating. To be able to pick the reflectors wherever
29 they are located throughout the seismic volume, the interpreter must be able to determine the vertical
30 displacement across faults, and above all, he must discriminate whether a discontinuity is due to noise or
31 artefacts or is evidence of a fault (Fig. 1).

32 As manual interpretation is both costly and subjective, some authors have investigated the use of image
33 processing to develop automatic approaches (Admasu and Toennies, 2004; Randen et al, 2001; Sønneland
34 et al, 2000). The resulting automatic tools are useful for structural interpretation of seismic data, but these
35 tools failed in tracking horizons across faults especially if the level of noise is high.

36 One way to improve the efficiency of both manual and automatic interpretation is to increase the quality of
37 the 3D seismic data by enhancing the structures to track as preserving the faults.

38 Among the different methods to achieve the denoising of 2D or 3D data, a large number of approaches
39 using non-linear diffusion techniques have been proposed in the recent years (Weickert, 1997). These
40 techniques are based on the use of Partial Differential Equations (PDE).

41 The simplest diffusion process is the linear and isotropic diffusion that is equivalent to a convolution with a
42 Gaussian kernel.

43

44 The similarity between such a convolution and the heat equation was proved by Koenderink (1984):

$$45 \quad \frac{\partial U}{\partial t} = c\Delta U = \operatorname{div}(c\nabla U) \quad (1)$$

46 In this PDE, U represents the intensity function of the data; c is a constant which, together with the scale of
47 observation t , governs the amount of isotropic smoothing. Setting $c=1$, (1) is equivalent to convolving the
48 image with a Gaussian kernel of width $\sqrt{2t}$. div indicates the divergence operator.

49 Nevertheless, the application of this linear filter over an image produces undesirable results, such as edge
50 and relevant details blurring.

51 To overcome these drawbacks Perona and Malik (1990) proposed the first non-linear filter by replacing the
52 constant c with a decreasing function of the gradient, such as:

$$53 \quad g(|\nabla U|) = \frac{1}{1 + (|\nabla U|/K)^2} \quad (2)$$

54 where K is a diffusion threshold. The diffusion process is isotropic for contrast values under the threshold
55 K ; gradient vector norms higher than K are producing edge enhancing. Despite the quite convincing
56 practical results, certain drawbacks remain unsolved: staircase effect (Whitaker and Pizer, 1993) or pinhole
57 effect (Monteil and Beghdadi, 1999) are often associated with the Perona Malik process. In addition, in the
58 strongly noised regions, the model may enhance the noise. Since the introduction of this first non-linear
59 filter, related works attempted to improve it (Catte et al, 1992).

60 Weickert (1994; 1995) proposed two original models with tensor based diffusion functions. The purpose of
61 a tensor based approach is to steer the smoothing process according to the directional information contained
62 in the image structure. This anisotropic behaviour allows for adjusting the smoothing effects according to
63 the direction.

64 The general model is written in PDE form, as:

$$65 \quad \frac{\partial U}{\partial t} = \text{div}(D\nabla U) \quad (3)$$

66 with some initial and reflecting boundary conditions.

67 In the Edge Enhancing Diffusion (EED) model, the matrix D depends continuously on the gradient of a
 68 Gaussian-smoothed version of the image (∇U_σ). The aim of this Gaussian regularization is to reduce the
 69 noise influence, having as result a robust descriptor of the image structure. For 2D application, the diffusion
 70 tensor D is constructed by defining the eigenvectors (\vec{v}_1) and (\vec{v}_2) according to $\vec{v}_1 \parallel \nabla U_\sigma$ and
 71 $\vec{v}_2 \perp \nabla U_\sigma$ (Weickert, 1994). The corresponding eigenvalues λ_1, λ_2 were chosen as:

$$72 \quad \begin{cases} \lambda_1 = \begin{cases} 1, & \text{if } |\nabla U_\sigma| = 0 \\ 1 - \exp\left(\frac{-1}{|\nabla U_\sigma|^2}\right), & \text{else} \end{cases} \\ \lambda_2 = 1 \end{cases} \quad (4)$$

73 In this manner, EED driven processes are smoothing always along edges ($\lambda_2 = 1$) and, in the direction of
 74 the gradient, the diffusion is weighted by parameter λ_1 according to the contrast level in that direction.

75 Besides the EED model which enhances edges, Weickert proposed also a model for enhancing flow-like
 76 patterns: the Coherence Enhancing Diffusion - CED - (Weickert, 1999). The structure tensor introduced in
 77 this model is a powerful tool for analyzing coherence structures. This tensor J_ρ is able to measure the
 78 gradient changes within the neighbourhood of any investigated point:

$$79 \quad J_\rho(\nabla U_\sigma) = K_\rho * (\nabla U_\sigma \otimes \nabla U_\sigma) \quad (5)$$

80 Each component of the resulted matrix of the tensor product (\otimes) is convolving with a Gaussian kernel
81 (K_ρ) where $\rho \gg \sigma$. The eigenvectors of J_ρ represent the average orientation of the gradient vector (\vec{v}_1)
82 and the structure orientation (\vec{v}_2), at scale ρ . The diffusion matrix D (3) has the same eigenvectors as J_ρ ,
83 but its eigenvalues are chosen according to a coherence measure. This measure is proposed as the square
84 difference between the eigenvalues of the structure tensor. The diffusion process acts mainly along the
85 structure direction and becomes stronger as the coherence increases. In this manner, the model is even able
86 to close interrupted lines.

87 Due to the characteristics of tensor D (symmetry and positive eigenvalues), well posedness and scale-space
88 properties were proved for both EED and CED models.

89 Based on these classical approaches, Terebes et al. (2002) proposed a new model, which takes advantage of
90 both scalar and tensor driven diffusions. The mixed-diffusion combines the CED model with an original
91 approach of the Perona Malik filter. The model aims at using the anisotropic diffusion in case of linear
92 structures and a scalar diffusion otherwise. In order to avoid the development of false anisotropic structures
93 and corner rounding (caused by the CED model), the scalar diffusion is applied to the regions with a noisy
94 background and to junctions. The decision between types of diffusion is taken with respect to the global
95 confidence proposed by Rao (1990). A strictly tensorial approach where the amount of diffusion was
96 weighted by a sigmoid function depending on the Rao confidence is proposed in Terebes et al (2005).

97 Concerning the 3D applications, anisotropic diffusion has been frequently used in medical image
98 processing. These works concern noise elimination (Gerig et al, 1992) but more often boundary detection
99 and surface extraction (Krissian et al, 1995; Dosil and Pardo, 2003). Recently, specific PDE-based
100 approaches were devoted to the seismic images filtering (Dargent et al, 2004a; Dargent et al, 2004b).

101 As we have seen, in most approaches an adaptive behaviour is obtained taking into account the local image
102 structure and more particularly the local orientation. Concerning the characterization of the local structure,
103 we have to mention the advanced works based on filter banks. These tools have proven efficient for
104 orientation analysis (Granlund and Knutsson, 1995). In particular the first efficient approach was the
105 steerable filters proposed by Freeman and Adelson (1991). Van Ginkel et al (1997) introduced an original
106 deconvolution scheme leading to a better angular resolution of a Gaussian filter. Martens (1997) presented
107 an application concerning the anisotropic noise reduction based on the sampled Hermite transform,
108 efficient to represent 1-D structures in image. More recently, Gauthier et al (2005) proposed an application
109 of a particular type of filter bank called “Complex Lapped Transform” for seismic data filtering. In this last
110 case, due to the computational cost and the non-separability of the proposed transform, the application
111 concerns only 2D slides of a 3D-Block. In addition, the authors conclude that the results have to be
112 improved in term of fault preserving.

113 Furthermore, another non-PDE-based technique dedicated to the denoising of seismic structures was
114 proposed by Bakker et al (1999). The authors combine edge preserving filtering with adaptive orientation
115 filtering. The adaptive orientation filter consists in an elongated Gaussian filter steered by the eigenvectors
116 of the structure tensor. Besides, a generalized Kuwahara filter, in which the window with higher confidence
117 value is taken as a result, is proposed as edge preserving filter. This method leads to an enhancement of the
118 faults when applied over the seismic images, but this enhancement is accompanied by a strong modification
119 of the seismic data. We can note that one interest of this approach lies in its low computational cost.

120 In this paper we present a new approach based on the CED model, dedicated to 3-D seismic blocks
121 processing. Seismic data are composed of strongly oriented patterns - stacks of almost parallel surfaces
122 broken by faults. The aim of our method is to deliver a 3-D accurate image, from the fault detection point
123 of view. So, our filtering consists in a data pre-processing method, which takes into consideration the
124 enhancing of relevant discontinuities.

125 In section II we present the general 3-D CED model and some specific improvements for seismic data. A
 126 measure will be chosen to steer the diffusion along different coherence structures, such as plane-like or
 127 line-like structures. Relevant results, for both synthetic and real images, will be illustrated in section III.
 128 Finally, conclusions and further work will be presented.

129 2. Seismic data enhancing using 3-d anisotropic diffusion

130 In this section, we present the extension of CED model in the 3-D case. Thanks to a confidence measure,
 131 we propose some improvements of this filter with respect to our type of data.

132 A. 3-D CED model

133 The 3-D model is a particular case of the general CED model (Weickert, 1995).

134 The structure tensor (5), becomes:

$$135 \quad J_{\rho}(\nabla U_{\sigma}) = K_{\rho} * \begin{pmatrix} \left(\frac{\partial U_{\sigma}}{\partial x}\right)^2 & \frac{\partial U_{\sigma}}{\partial x} \frac{\partial U_{\sigma}}{\partial y} & \frac{\partial U_{\sigma}}{\partial x} \frac{\partial U_{\sigma}}{\partial z} \\ \frac{\partial U_{\sigma}}{\partial x} \frac{\partial U_{\sigma}}{\partial y} & \left(\frac{\partial U_{\sigma}}{\partial y}\right)^2 & \frac{\partial U_{\sigma}}{\partial y} \frac{\partial U_{\sigma}}{\partial z} \\ \frac{\partial U_{\sigma}}{\partial x} \frac{\partial U_{\sigma}}{\partial z} & \frac{\partial U_{\sigma}}{\partial y} \frac{\partial U_{\sigma}}{\partial z} & \left(\frac{\partial U_{\sigma}}{\partial z}\right)^2 \end{pmatrix} \quad (6)$$

136 The smoothed version of intensity (U_{σ}) is obtained after a convolution with a 3-D Gaussian kernel:

$$137 \quad K_{\sigma}(u) = \frac{1}{(2\pi\sigma^2)^{3/2}} \cdot \exp\left(-\frac{u^2}{2\sigma^2}\right) \quad (7)$$

138 The *noise scale* (σ) establishes the minimum size of the objects preserved in the smoothed image. An
 139 average of the orientation, at *integration scale* ρ , is applied to deliver the orientation of the significant
 140 structures. Usually, the integration scale is chosen larger than the noise scale.

141 Due to the structure tensor properties (symmetric positive semi-definite), the eigenvalues are real and
 142 positive. These may be ordered as follows:

$$143 \quad \mu_1 \geq \mu_2 \geq \mu_3 \quad (8)$$

144 The corresponding eigenvectors $(\vec{v}_1, \vec{v}_2, \vec{v}_3)$ form an orthogonal system. The largest eigenvalue carries the
 145 contrast variation in the dominant orientation of the averaged gradient vector (\vec{v}_1) . The orientation
 146 corresponding to the lowest contrast difference is indicated by the third vector (\vec{v}_3) .

147 Weickert introduces this knowledge of orientation in the general anisotropic model (3). Matrix D has the
 148 same eigenvectors as the structure tensor. The orientation of the diffusion is driven by these eigenvectors
 149 and the intensity of the process by the eigenvalues of D . The author proposes the following system for
 150 choosing the eigenvalues of matrix D :

$$151 \quad \begin{cases} \lambda_1 = \lambda_2 = \alpha \\ \lambda_3 = \begin{cases} \alpha & \text{if } k = 0 \\ \alpha + (1 - \alpha) \exp\left(\frac{-C}{k}\right) & \text{otherwise} \end{cases} \end{cases} \quad (9)$$

152 The parameter α represents the amount of diffusivity in the orientations of the highest fluctuation
 153 contrast. In order to hamper the diffusion in these orientations, the parameter α is chosen nearly 0. For
 154 theoretical reasons this parameter must be positive.

155 The measure of coherence k is defined as:

$$156 \quad k = (\mu_1 - \mu_2)^2 + (\mu_1 - \mu_3)^2 + (\mu_2 - \mu_3)^2 \quad (10)$$

157 The threshold parameter C is usually chosen equal to 1. In the coherent structures ($k \gg C$), the diffusion
 158 processes essentially along \vec{v}_3 ($\lambda_3 \approx 1$). On the other hand, if the structure becomes isotropic ($k \rightarrow 0$), the
 159 amount of diffusivity in all three orientations is no more than α .

160 This coherence measure k depends on the gradient energy. For this reason, the amount of diffusivity (λ_3)
 161 in the third vector orientation always tends to 1. In conclusion, this system will smooth only in one
 162 orientation of space, which is not adapted to seismic data.

163 In order to deal with plane-like structures like seismic horizons, the first idea consists in forcing the
 164 diffusion process along both the second and third eigenvectors. We can easily obtain such a result by
 165 choosing a set of eigenvalues different from (9):

$$166 \quad \begin{cases} \lambda_1 = \alpha \\ \lambda_2 = \lambda_3 = \begin{cases} \alpha & \text{if } k = 0 \\ \alpha + (1 - \alpha) \exp\left(\frac{-C}{k}\right) & \text{otherwise} \end{cases} \end{cases} \quad (11)$$

167 In the result section, the original weickert's approach will be denoted CED-1D and the approach based on
 168 this new set of eigenvalues will be denoted CED-2D as it allows filtering of 2D structures.

169 Using the CED-2D approach leads to a diffusion process steered along the 2D horizons even in the
 170 presence of faults. As a consequence, this method presents the drawback of smoothing the signal across
 171 faults leading to a loss of relevant seismic information.

172 Considering the behaviour of the CED-1D and CED-2D methods, we will propose a new approach which
 173 consists in choosing an appropriate set of eigenvalues to both enhancing the structures to track and
 174 preserving the faults as relevant details.

175

177 *B. Confidence measures for seismic data*

178 Among important features of seismic 3-D data, faults represent an interesting point for our treatment. A
 179 simplified view describes the seismic data like stacks of almost parallel planes (horizons) broken by faults.
 180 We may interpret these strongly oriented data as linear structures. Van Kempen et al (1999) define the
 181 notion of dimensionality of structures. In 3-D case, beside the isotrope structures corresponding to three
 182 shift invariant orientations, two types of linear structures are possible:

- 183 • plane-like linear structure – shift invariant along two orientations,
- 184 • line-like linear structure – shift invariant along one orientation.

185 Analysis of the linear structure may be issued by the computation of the structure tensor. Thus, the vectors
 186 of the structure tensor point out the principal axes of orientation and the number of the zero eigenvalues
 187 indicates the number of the shift invariant orientations.

188 In the seismic case, the horizons can be viewed as plane-like structures. A horizon is characterized by a
 189 large eigenvalue and two others close to zero. A fault is characterized by two large eigenvalues and the
 190 other close to zero. This property is due to the fact that the orientation of the average gradient around the
 191 fault is a mixture of two distinct orientations corresponding to the neighbourhood regions. Thus, we can
 192 model the fault as a line-like structure, although, from a seismic point of view, it is rather a plane than a
 193 line.

194 In 2001, Bakker et al, following the works of Bigun et al (1991), proposed two measures to estimate the
 195 semblance of seismic data with this type of linear structures:

$$196 \quad C_{plane} = \frac{\mu_1 - \mu_2}{\mu_1 + \mu_2} \quad C_{line} = \frac{\mu_2 - \mu_3}{\mu_2 + \mu_3} \quad (11)$$

197 These measures are combined to obtain a fault confidence:

$$198 \quad C_{fault} = C_{line} (1 - C_{plane}) \quad (12)$$

199 We can note that the author proposes to introduce this measure as a confidence value to select the optimal
200 mask in an approach combining orientation adaptive filtering and edge preserving filtering. The
201 introduction of such a priori measures leads to a technique which strongly enhances the detected faults. The
202 more serious drawback of this approach is that it leads to a too important data transformation.

203

204 *C. Seismic Fault Preserving Diffusion*

205 We propose a new approach of the general CED model, more appropriate for seismic data. Keeping the
206 general equation of the anisotropic diffusion (3) we introduce an adaptive system to fix the D matrix
207 eigenvalues.

208 We intended to create a system adapted to local context, which acts in specific ways for different regions.
209 We chose the confidence measure C_{fault} from the various set of measures dedicated to this purpose (Rao,
210 1990; Berthoumieu, 2006). The reason why we selected this type of measure is its closed link to the nature
211 of our seismic data. We propose the following system:

$$212 \quad \begin{aligned} \lambda_1 &= \alpha \\ \lambda_2 &= \lambda_3 - (\lambda_3 - \lambda_1) h_\tau(C_{fault}) \\ \lambda_3 &= \begin{cases} \alpha & \text{if } k = 0 \\ \alpha + (1 - \alpha) \exp\left(\frac{-C}{k}\right) & \text{else} \end{cases} \end{aligned} \quad (13)$$

213 where $h_\tau(s)$ is described in (Terebes et al., 2005):

$$214 \quad h_\tau(s) = \frac{\tanh[\gamma(s - \tau)] + 1}{\tanh[\gamma(1 - \tau)] + 1} \quad (14)$$

215 The eigenvalue λ_2 depends continuously on the confidence measure (C_{fault}) and takes values
216 between λ_1 and λ_3 . In the neighbourhood of a fault, λ_2 tends to λ_1 whereas it tends to λ_3 when $C_{fault} \rightarrow 0$.
217 Through the value of two parameters the threshold τ and the slope γ , the sigmoid function $h_\tau(s)$ allows a
218 better control of transition between two homogeneous regions.

219 Within presumptive fault zones ($C_{fault} \rightarrow 1$), the process will only smooth along the smallest variation of
220 contrast (\vec{v}_3). In this case the amount of diffusivity in the first and in the second orientation given by the
221 λ_2 and λ_1 values is equal to α chosen near to 0.

222 The regions where $C_{fault} \rightarrow 0$ are rather characterized by plane-like structures ($C_{plane} \rightarrow 1$). In these
223 regions the process will diffuse in the plane defined by the vectors \vec{v}_2 and \vec{v}_3 . This plane is orthogonal to
224 the average gradient. For this type of horizons the coherence measure k is high ($\mu_1 \gg \mu_2 \approx \mu_3$) and forces
225 the λ_2 and λ_3 values to reach 1.

226 3. Results

227 This section illustrates the efficiency of our approach on both synthetic and real seismic blocks. The
228 noise reduction and the faults preserving are evaluated. Our filter is compared with both the CED-1D and
229 CED-2D models.

230 3.1. 3D-synthesized blocks

231 Since it is much easier to judge the efficiency of the algorithms on a synthetic image, we propose to use a
232 3-D synthetic block composed by a stack of layers with a sinusoidal profile and broken by two crossed
233 faults. Figure 2 shows a front section of the original block.

234 The data are corrupted with additive Gaussian white noise. Figure 3 shows the noisy blocks for signal-to-
 235 noise-ratio (SNR) of 1 dB, 3 dB and 5 dB. Each noisy block is filtered with our method and the CED
 236 methods. Parameters common to the various algorithms take on the same values
 237 ($dt=0.05, \sigma = 0.4, \rho = 1.2, \alpha = 10^{-4}, 120 \text{ iterations}$). In addition, parameters specific to SFPD are set to
 238 $\tau = 0.1$ and $\gamma = 10$. We show in Figure 4 the results obtained using an explicit numerical scheme.

239 Figure 5 shows the top views (i.e. time slices) corresponding to the SFPD and both CED results for the 3
 240 dB noisy block.

241 The efficiency of our method was evaluated by the means of root-mean-square-error (RMSE) which
 242 allows quantifying the similarity between each diffused block and the original synthetic block:

$$243 \quad RMSE = \sqrt{\frac{\sum_{x,y,z} (U(x, y, z) - U_0(x, y, z))^2}{n}} \quad (15)$$

244 where U_0 denotes the value of the voxel with coordinates (x,y,z) in the original non-noisy block (Fig. 2)
 245 and U the value of the same voxel in the processed image. n denotes the total number of voxels.

246 Firstly, the original block was segmented in two regions: faults and non-faults. This segmentation was
 247 achieved using a simple thresholding on the C_{fault} value. Then, for each processed block, the RMSE has
 248 been computed in these two different zones in order to illustrate the behaviour of the methods in particular
 249 in the fault regions. The resulting RMSE values are provided in Table 1.

250 Considering the quality of the denoising, our approach performs well when compared with the CED
 251 models, in terms of both visual quality and global RMSE. In particular, false anisotropic structures appear
 252 in the block processed with the CED 1D model (Fig. 5c) while our approach does not create this type of
 253 structure (Fig. 5d). This is also reflected in the RMSE values corresponding to the non-fault region.

254 Like our model, CED 1D preserve the faults producing comparable RMSE values in fault region, which
255 is not the case of CED 2D model. On the other hand CED 2D model provides a good quality in the non-
256 fault zones (Fig. 4c, 4f, 4i).

257 Finally, considering both the noise reduction and the fault preserving, we can conclude that the proposed
258 SFPD model takes advantage of the 1D and 2D Weickert's models.

259 *3.2. Real 3D-reflection seismic data*

260 Figure 6 compare results generated on a real seismic block (Fig. 1) by CED 1D, CED 2D and SFPD
261 respectively. These results illustrate that SFPD is better adapted to remove the noise while preserving the
262 fault.

263 **4. Conclusions**

264 We have proposed a new approach of tensorial diffusion which takes into account the characteristics of
265 seismic data. More precisely, we make sure that our denoising approach preserves the faults. For this
266 purpose we use a measure of fault confidence in a tensor driven diffusion process adapted to the local
267 context. This measure allows us to diffuse only in one orientation in a fault neighbourhood and to perform a
268 diffusion process guided by two orientations along the layers otherwise. This approach also exempts from
269 the creation of false anisotropic structures, artefacts typically observable in images processed with the
270 classical tensorial models. Our method can be used as a preprocessing for automatic or manual
271 interpretation of 3D reflection seismic data.

272 Future works will focus on improving our model by adding more seismic-data-specific properties.

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Original SNR values (dB)	Methods	RMSE		
		Fault regions	non-Fault regions	Whole block
1.0	SFPD	14.548	7.560	8.569
	CED 1D	16.629	14.370	14.628
	CED 2D	18.648	7.412	9.564
3.0	SFPD	11.523	3.893	5.002
	CED 1D	11.681	7.837	8.247
	CED 2D	18.113	5.205	8.037
5.0	SFPD	10.930	2.835	4.067
	CED 1D	10.330	5.582	6.109
	CED 2D	18.058	4.622	7.691

Table 1. RMSE values for the diffusion of noisy synthesized 3D-blocks in both fault and non-fault regions.

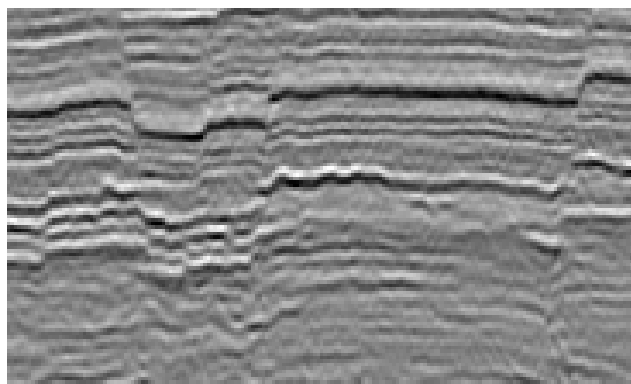


Figure 1: A section of 3D seismic data

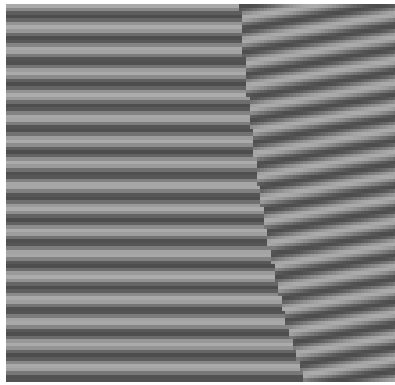


Figure 2: Front section of a synthesized block

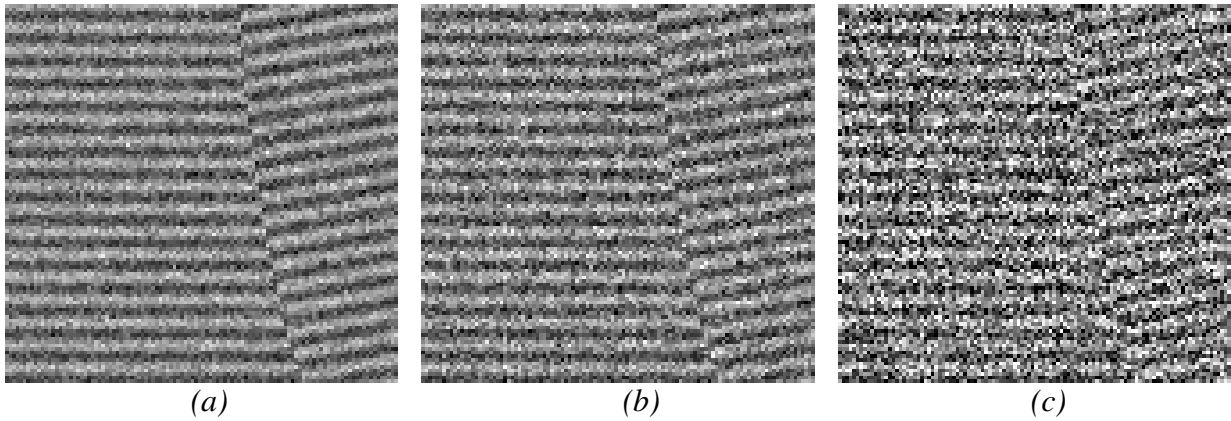


Figure 3: Front section of noisy synthesized 3D-blocks. SNR= (a) 5dB (b) 3dB (c) 1dB

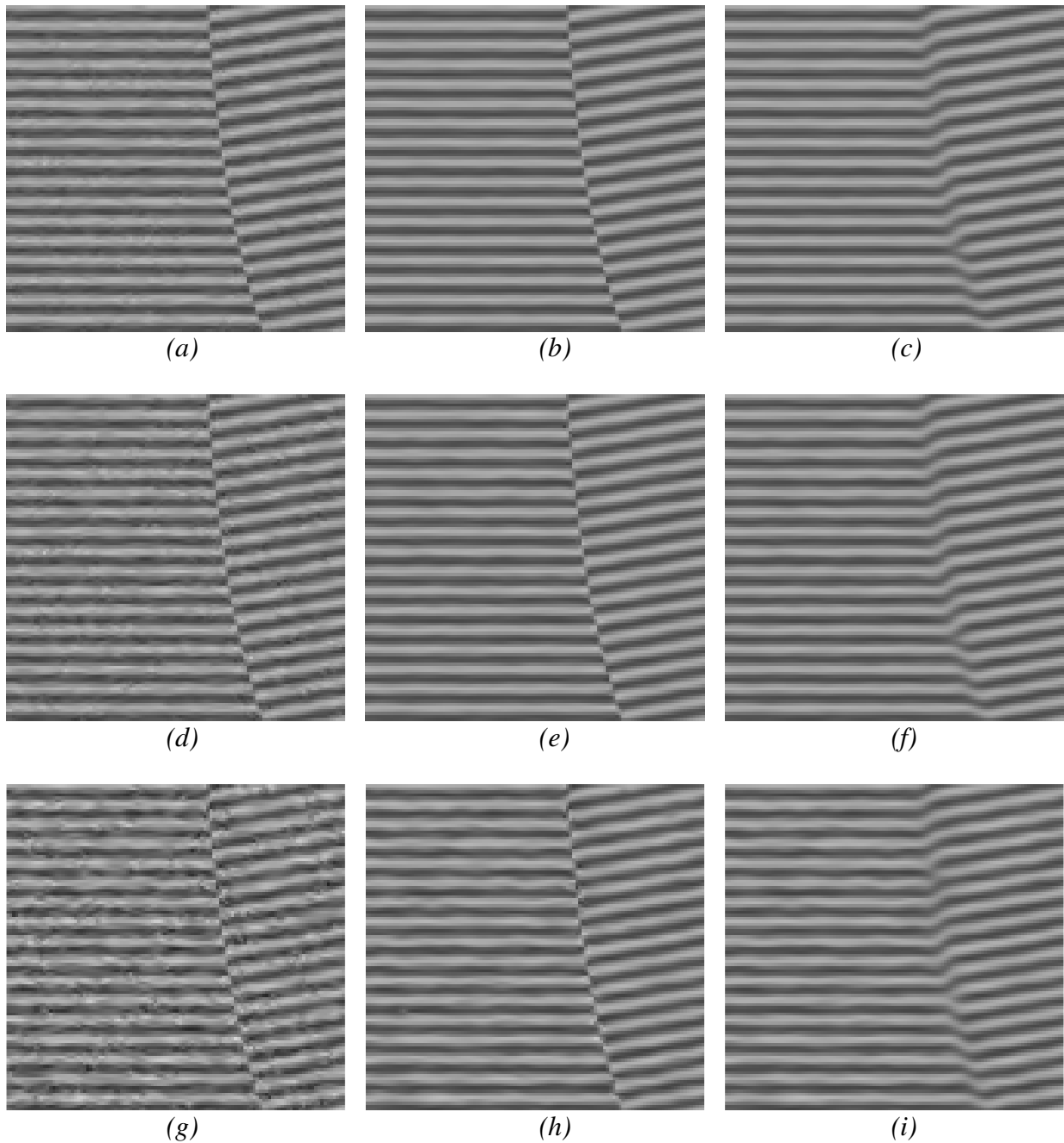


Figure 4: Diffusion Results for synthesized block. First row: diffusion of the noisy block with SNR=5dB (a) CED 1D, (b) SFPD, (c) CED 2D ; second row: diffusion of the noisy block with SNR=3dB: (d) CED 1D, (e) SFPD, (f) CED 2D ; third row: diffusion of the noisy block with SNR=1dB: (g) CED 1D, (h) SFPD, (i) CED 2D.

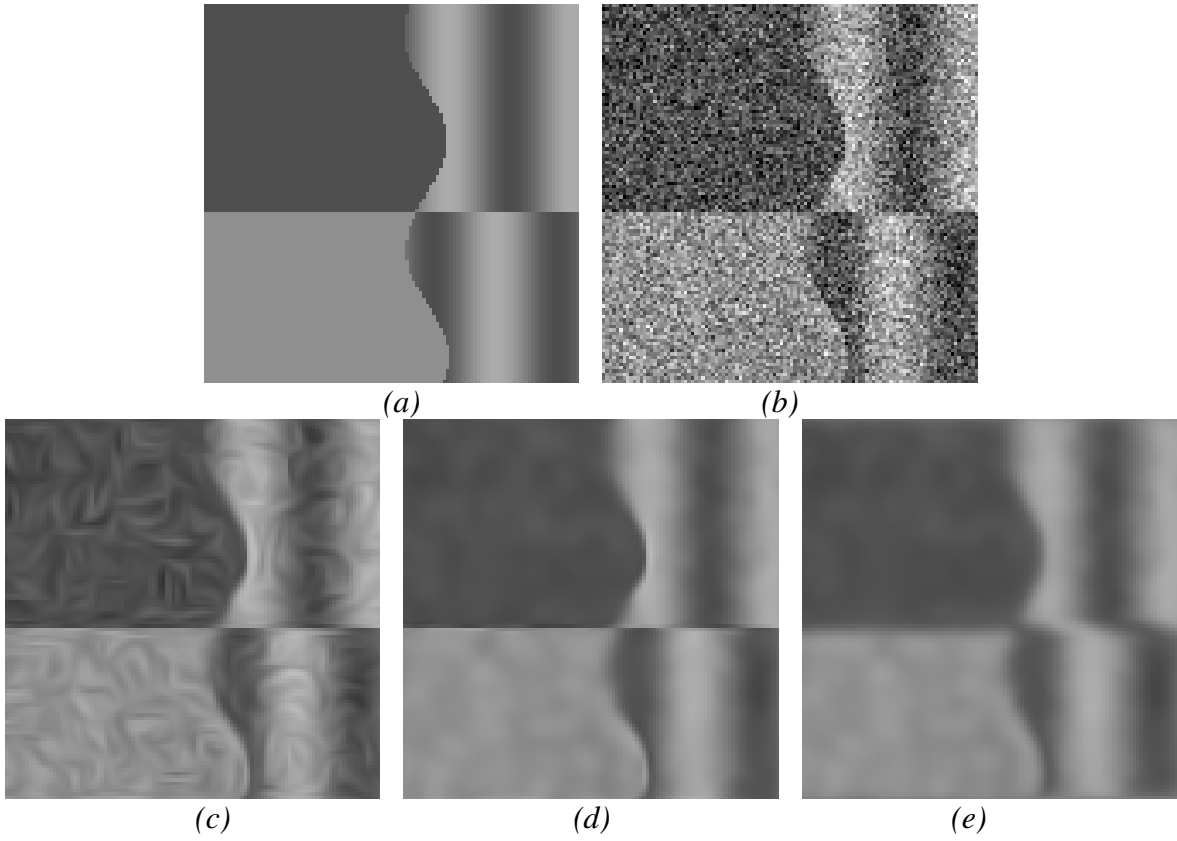
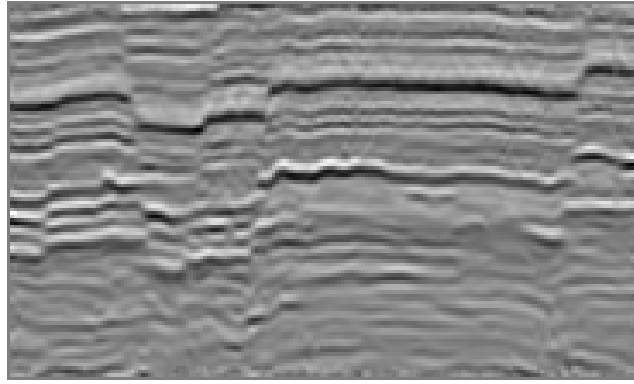
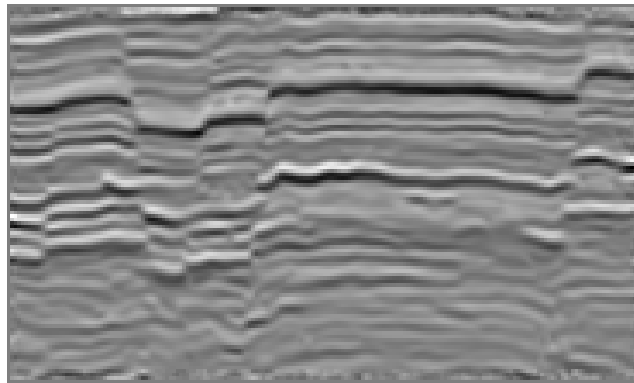


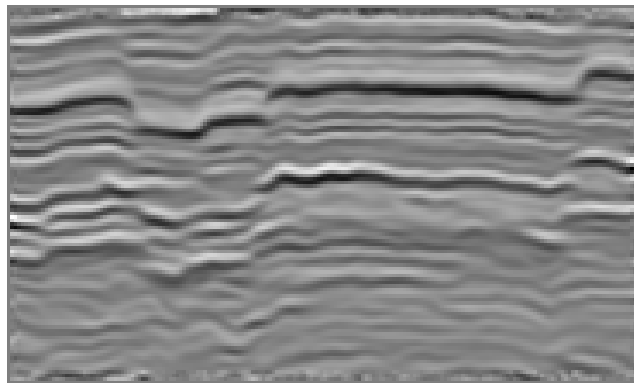
Figure 5: Top view of diffused blocks. (a) Original (b) noisy-SNR=3dB (c) CED 1D-diffusion
(d) SFPD diffusion (e) CED 2D diffusion



(a)



(b)



(c)

Fig.6 Diffusion Results for the real 3D seismic block. (a) CED 1D diffusion (b) SFPD-diffusion

(c) CED 2D-diffusion