3D CRS ATTRIBUTE SEARCH USING PARTICLE SWARM OPTIMIZATION

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ABSTRACT

Previous determination of the initial 3D CRS attributes was steered by the pragmatic three-step grid search. However, this search method applies a grid search strategy at each step, which makes this method very expensive while increasing the number of grid points. Furthermore, the final results hardly improve even if the number of grid points in each search step is increased since only small subsets of the entire CRS traveltime surface are used in this approach. To circumvent this problem, we introduce the particle swarm optimization (PSO) algorithm to simultaneously search the initial 3D CRS attributes. For comparing both search methods, the 3D SEG WA synthetic data set is used.

INTRODUCTION

The CRS stack method has become an alternative method to the NMO/DMO stack for many years (Müller, 1999, Jäger et al., 2001 and Mann, 2002). It is a data-driven and macro velocity model independent stacking operator to obtain a high S/N ratio and high-quality seismic images combining neighbouring CMP gathers/volumes. In 2D case, the classic CRS stack operator is a second-order hyperbolic traveltime approximation (Tygel et al., 1997), which depends on three kinematic wavefield attributes. When extending to 3D, the stacking operator is determined by eight attributes (e.g., Höcht, 2002 or Müller, 2007). In previous determinations of the initial 3D CRS attributes the so called pragmatic approach (PA), a three-step grid search was used. However, this search strategy is expensive while increasing the number of grid points in each step, particularly in the searching of elements of two wavefront curvature matrices. For example in the normal-wave wavefront curvature matrix search: Using 100 intervals for each element of the curvature matrix results in 1.000.000 function evaluations. In addition, the pragmatic three-step grid search is only using a subset of the entire CRS traveltime surface, i.e., the full stacking power of the CRS method is not exploited even if we increase the number of grid points in each step. The particle swarm optimization (PSO) is introduced as an alternative optimization strategy in this paper to circumvent this problem. PSO is a global simultaneous determination procedure for the initial 3D CRS attributes which uses the entire 3D CRS traveltime surface. Usually only $20 \sim 40$ particles are used in the PSO. Here we focus on sharing this new simple solution to obtain the initial 3D CRS attributes and no subsequent local optimizations are discussed. Finally, we compare results of the PA and PSO methods using the 3D SEG WA data set as an example.

THEORY

3D CRS

The mostly used 3D CRS operator is a second-order traveltime approximation which reads:

$$t_{hyp}^2 = (t_0 + \frac{2}{v}\,\mathbf{w}_z \cdot \mathbf{m})^2 + \frac{2t_0}{v}\mathbf{m^T T \hat{N} T^T m} + \frac{2t_0}{v}\,\mathbf{h^T T \hat{M} T^T h}. \quad (1)$$

where υ is the near-surface velocity, $\mathbf{w}_z$ involves two angles, **m** is midpoint displacement, **h** is half-offset,**T** is the upper left 2×2 submatrix of the 3×3 transformation matrix, and $\hat{\mathbf{N}}$ and $\hat{\mathbf{M}}$ are related to two wavefront curvature matrices (e.g., Höcht, 2002).

PSO

The PSO method is originally attributed to Kennedy and Eberhart (1995) and Shi and Eberhart (1998). It has been intensively studied in engineering, mathematics, as well as computer sciences in recent years. It is a meta-heuristic algorithm, which updates the particles' position (value) individually over the particle's velocity (variation) and chooses/keeps the particle with the best fitness (best solution) in memory. Its initial form can be expressed as:

$$\mathbf{v}_{i,j} = \eta\,\mathbf{v}_{i,j} + c_1\,r_1(\mathbf{p}_{i,j} - \mathbf{x}_{i,j}) + c_2\,r_2(\mathbf{g}_i - \mathbf{x}_{i,j}), \tag{2}$$

$$\mathbf{x}_{i,j} = \mathbf{x}_{i,j} + \mathbf{v}_{i,j}. \tag{3}$$

where

- $\mathbf{v}_{i,j}$ means the rate of velocity of each particle j , and i is dimensional index,
- $\mathbf{x}_{i,j}$ represents each particle's position,
- η is the inertia weight that can balances the global and local search,
- $\mathbf{p}_{i,j}$ is the previous best position of each particle,
- $\mathbf{g}_i$ indicates the global best during all particles,
- c_1 and c_2 are two positive constants, generally being set as constant 2,
- r_1 and r_2 are two random values between [0,1].

The workflow of our simultaneous search by the PSO method can be summarized as follow:

1. Set the maximum number of iterations
2. Initialize attribute positions (AP) in the search space for every attribute
3. Initialize the best attribute position (BAP) in the search space for every attribute
4. Calculate semblance for each individual
5. Calculate the global best position (GBP) based on the best fitness
6. Calculate each attribute's variation (velocity) according to equation (2)
7. Update each attribute's value (position) according to equation (3)
8. Update BAP and GBP if the new AP has better fitness
9. Abort criteria is semblance threshold or maximum iterations

In the above search strategy, the $\mathbf{v}_{i,j}$ and $\mathbf{x}_{i,j}$ should be constrained within a a user defined search space. The parameters c_1 and c_2 are defined as 2 according to a previous study (Shi and Eberhart, 1998). They can be modified using loops or vectors in the 3D CRS PSO code and finally suitable values for c_1 and c_2 for each ZO sample in the data set are found. But the loop search procedure is computationally very expensive. For the determination of initial CRS attributes, using 2 as the constant parameter for c_1 and c_2 is usually sufficient in most of cases. The implementation of the method with CRS used in this paper is part of the WIT software repository.

RESULTS

The simultaneous search method was tested on the well-known 3D SEG WA data set. The model of this data set contains a tetrahedron-like salt body with a velocity of nearly 4000 m/s below an overburden. The data set consists of 26 sail lines with intervals of 320 m. There are 96 shots per line with a 80 m shot interval comprising 8 cables per shot, 80 m cable separation, 68 receivers per cable, and 40 m receiver separation. Random Gaussian noise with S/N = 10 was added to the seismograms. For the comparison of both methods, we show one section out of the 3-D volume.

The parameters $\mathbf{M10}$ and $\mathbf{M11}$ used in this work represent two of elements of the matrix $\frac{2t_0}{v}\mathbf{T}\hat{\mathbf{M}}\mathbf{T}^{\mathbf{T}}$. Figure 1(a) and Figure 1(b) displays the results for $\mathbf{M10}$ obtained by both methods. In this comparison, we can see that the $\mathbf{M10}$ attribute section obtained by the PSO approach is considerably improved compared to pragmatic approach. Figure 2(a) and Figure 2(b) show the $\mathbf{M11}$ results obtained by both methods. Obviously simultaneous search by the PSO method provide smoother and more continuous results.

Figure 3(b) and Figure 3(a) show the result of $\mathbf{wz1}$, one element of the matrix $\frac{2}{v}\mathbf{w}_z$. We can see that the events of azimuths obtained by the PSO method are more continuous, and the image quality is also improved. These phenomena can also be observed in Figure 4(b) and Figure 4(a). The simultaneous search by the PSO method delivers an improved image of the attribute.

The semblance section shown in Figure 5(b) is the result obtained by the PSO method, which shows more smooth and better image, especially the right middle part, compared to the one obtained by the pragmatic approach shown in Figure 5(a). Therefore we conclude that the travel time surface determined by the improved attributes of the PSO approach better fit the events in the data.

CONCLUSIONS AND DISCUSSIONS

We moved away from the pragmatic approach into a global simultaneous PSO search for the determination of the initial 3D CRS attributes. As the entire traveltime surface is used in the PSO search strategy, the simultaneous PSO is more efficient and the resulting images are improved. In our tests for both methods the same initial input parameters, e.g., apertures, were used. In this work, we focused on the determination of the initial 3D CRS attributes. No subsequent optimizations to refine these initial attributes are discussed here. We will discuss the global optimization methods in a follow-up report.

The PSO as described in this paper can also be used for the 2D CRS search. Only one reflection dip is considered in current implementation. Obviously the simultaneous search in 3D CRS is more expensive than for 2D CRS. To increase computational efficiency, the implementation on a cluster with many CPU's and a hybrid parallelization is suggested.

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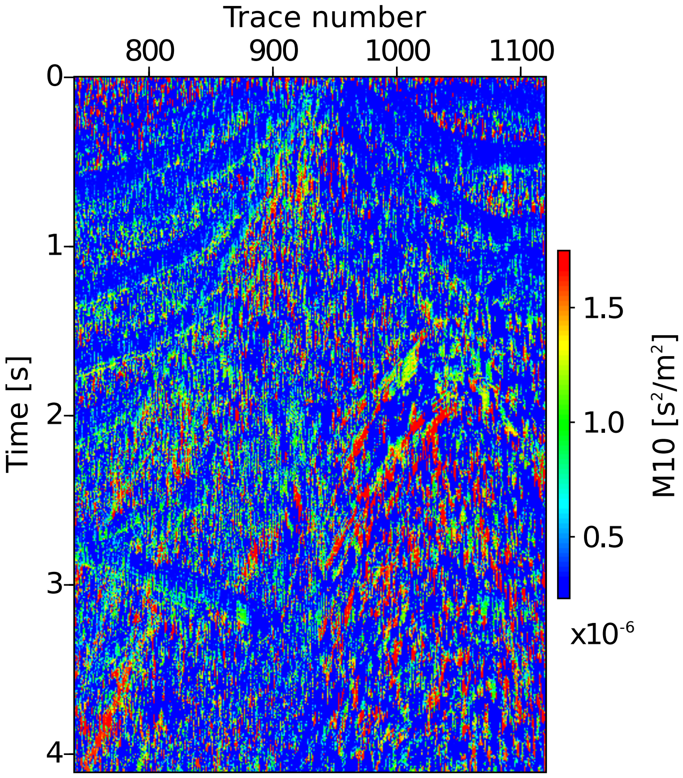
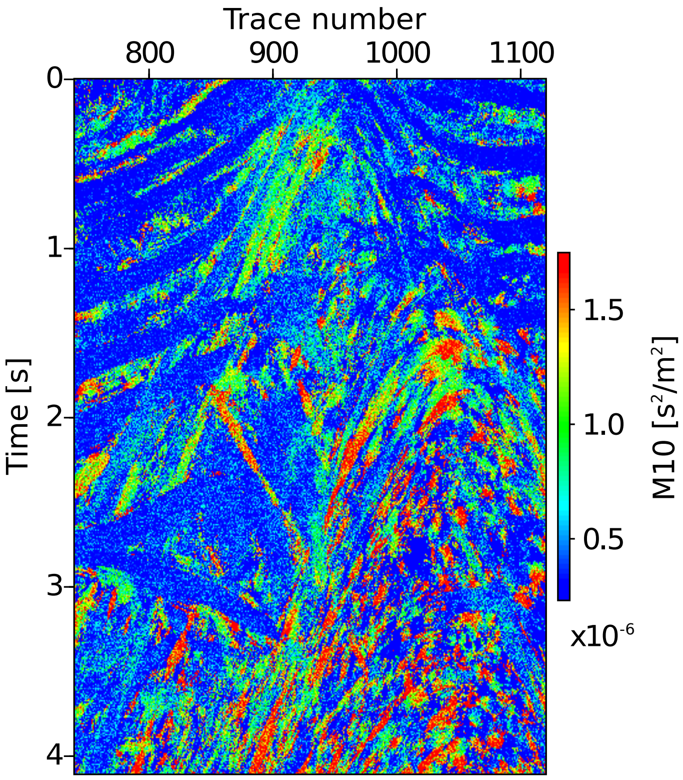
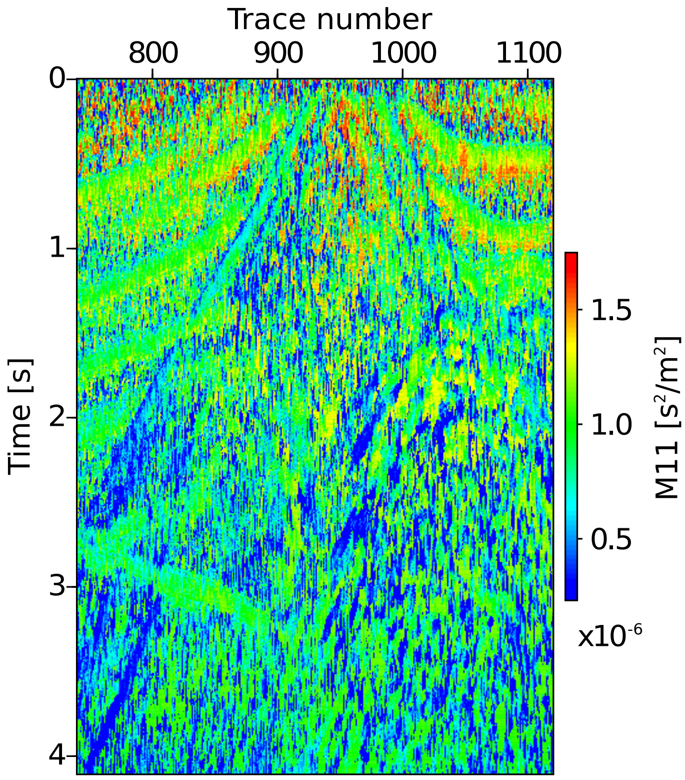


(a)

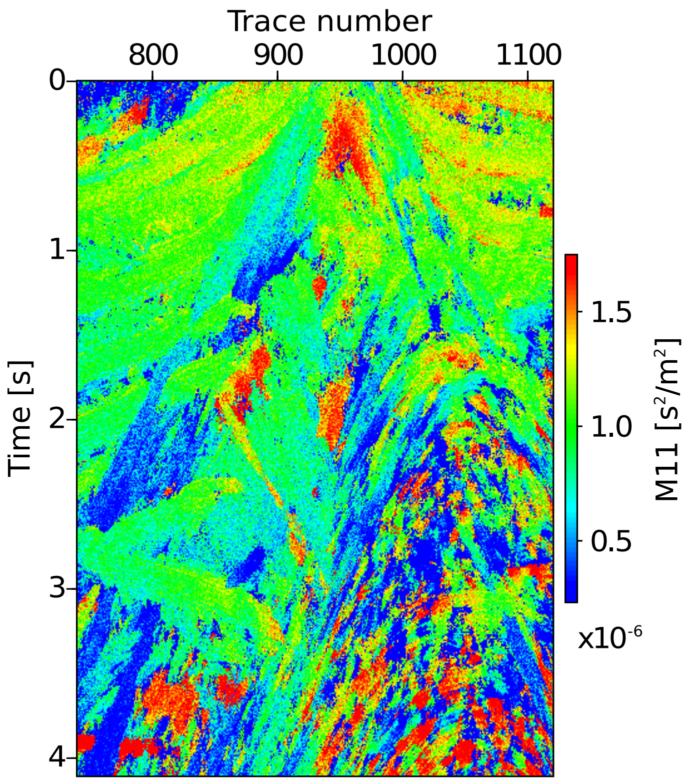


(b)

Figure 1: M10 results obtained by the pragmatic approach (a) and the simultaneous PSO method (b).

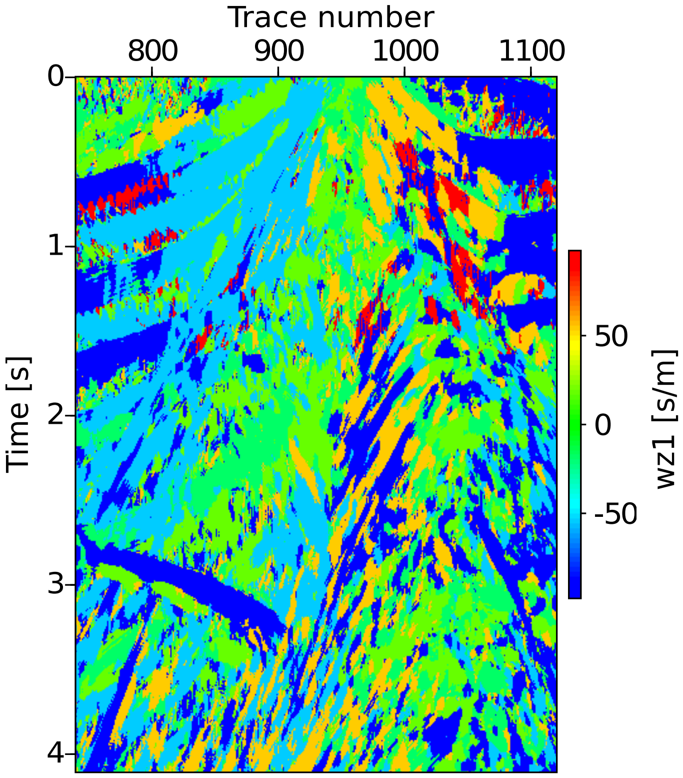


(a)

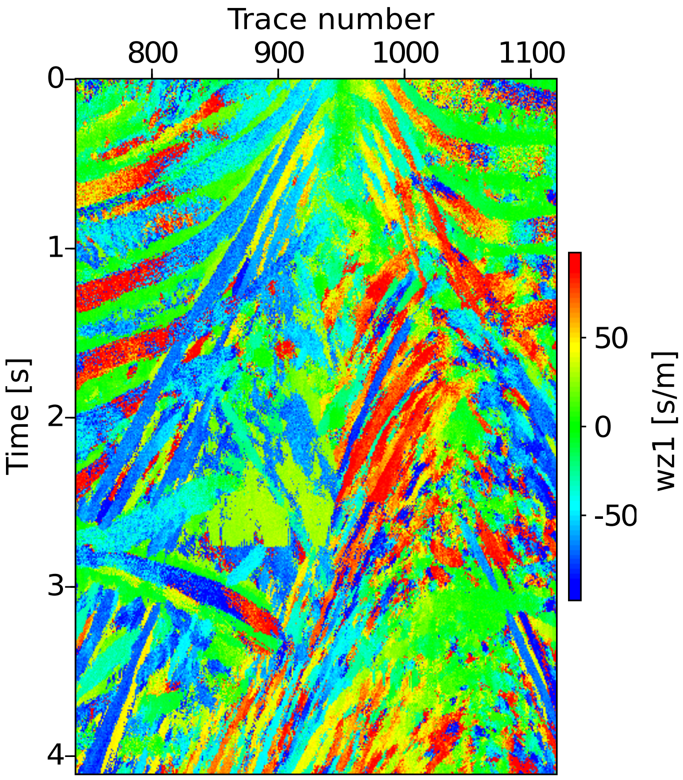


(b)

Figure 2: M11 results obtained by the pragmatic approach (a) and the simultaneous PSO method (b).

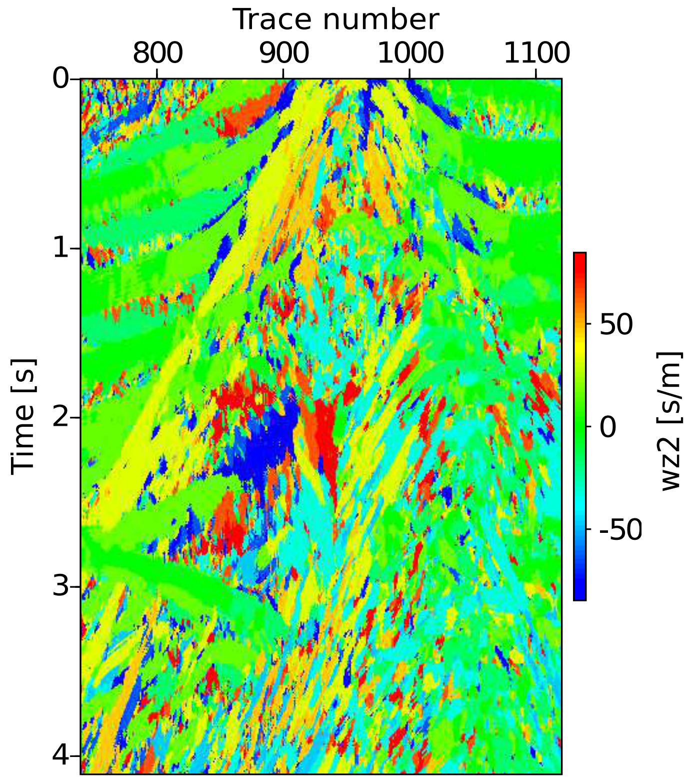


(a)

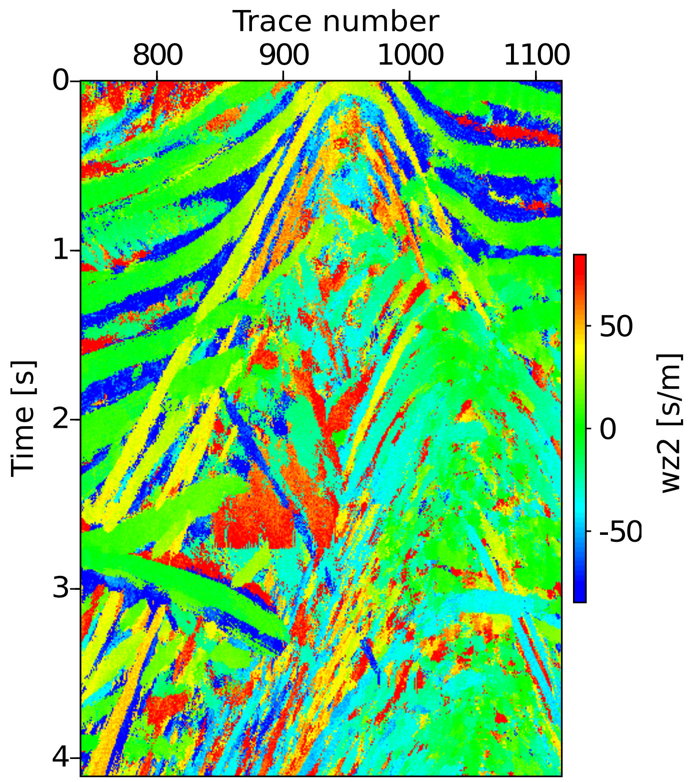


(b)

Figure 3: wz1 results obtained by the pragmatic method (a) and the simultaneous PSO method (b).

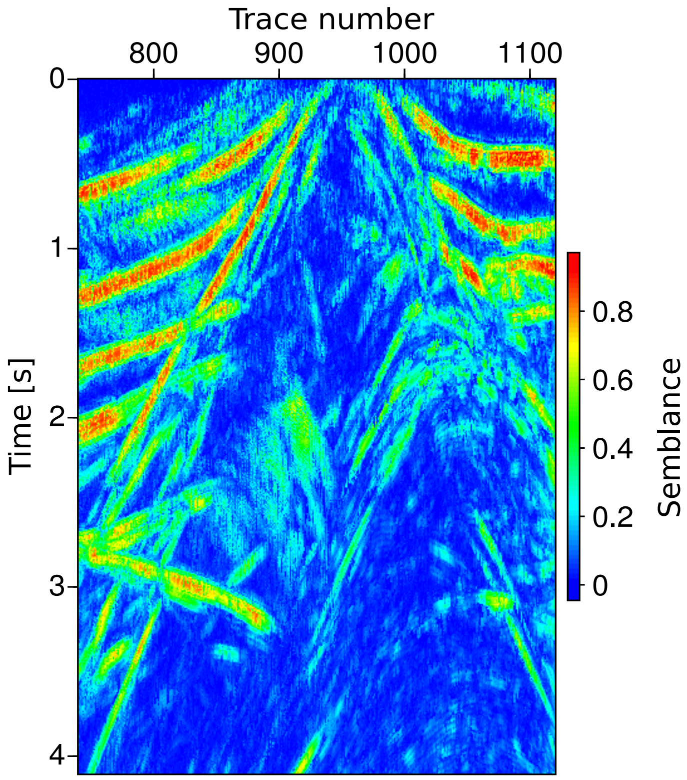


(a)

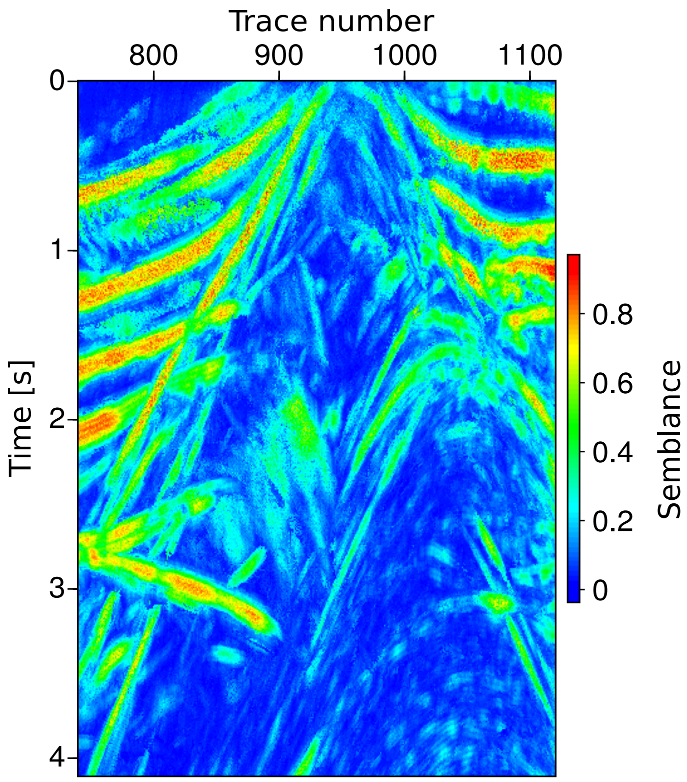


(b)

Figure 4: wz2 results obtained by the pragmatic method (a) and the simultaneous PSO method (b).



(a)



(b)

Figure 5: Semblance obtained by the pragmatic method (a) and the simultaneous PSO method (b).