

# Recursive stack to zero offset along local slope

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by:

**Michelângelo G. da Silva**

*UFBA - Salvador, Brazil*

**Milton J. Porsani**

*UFBA - Salvador, Brazil*

**Bjorn Ursin**

*NTNU - Trondheim, Norway*



## OVERVIEW

- ▶ Introduction
- ▶ Local data derivatives
- ▶ Least squares slopes
- ▶ Total least squares slopes
- ▶ Stacking along local slopes
- ▶ Stacking along the NMO velocity slope
- ▶ Automatic slope stack
- ▶ Data examples
- ▶ Conclusions

## INTRODUCTION

### ► **Standard data processing**

- Velocity analysis
- NMO correction
- Stack
- Mute to avoid stretch effects

### ► **Velocities independent seismic processing**

- Estimation of local slope (Fomel, 2007, Schleicher et al., 2009)

## LOCAL DATA DERIVATIVES

$$\frac{\partial d(t_i, x_j)}{\partial t} \approx Dt(t_i, x_j)$$

$$\frac{\partial d(t_i, x_j)}{\partial x} \approx Dx(t_i, x_j)$$

Computed from data points in a small neighborhood around  $(t_i, x_j)$  (Melo et al., 2007)

## LOCAL SLOPE

$$\frac{\partial d}{\partial t} \Delta t + \frac{\partial d}{\partial x} \Delta x = 0 \quad (\text{plane wave})$$

or

$$pDt_k + Dx_k = 0 \quad \text{with} \quad p = \frac{dt}{dx}.$$

Alternatively,

$$Dt_k + qDx_k = 0 \quad \text{with} \quad q = \frac{dx}{dt}.$$

## LEAST SQUARES I

Minimize

$$\phi_t = ||e_t||^2 = \sum_k |pDt_k + Dx_k|^2 = ap^2 + 2cp + b$$

with

$$a = \sum_k |Dt_k|^2$$

$$b = \sum_k |Dt_x|^2$$

$$c = \sum_k Dt_k Dx_k$$

The result is

$$\hat{p} = -\frac{c}{a}$$

## LEAST SQUARES II

With  $q = \frac{dx}{dt}$  minimize

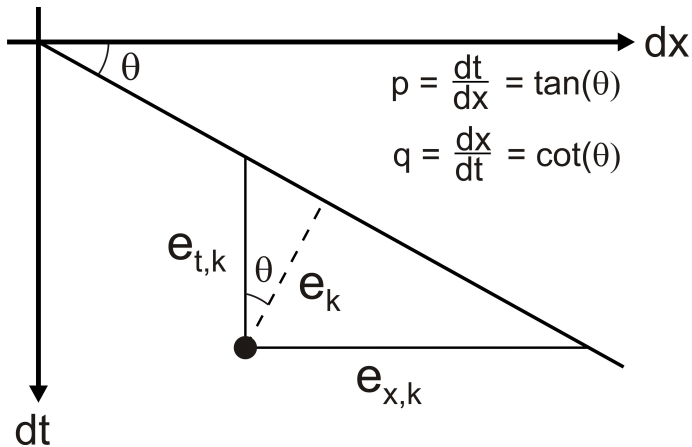
$$\phi_x = ||e_x||^2 = \sum_k |qDx_k + Dt_k|^2 = bq^2 + 2cq + a$$

The result is  $\hat{q} = -\frac{c}{b}$

Note that  $\hat{p}\hat{q} = \frac{c^2}{ab}$

Should have  $\frac{dt}{dx} \frac{dx}{dt} = 1$ .

## GEOMETRY OF TOTAL LEAST SQUARES





## TOTAL LEAST SQUARES I

Minimize  $\phi_p = \|e\|^2 = \|e_t\|^2 \cos^2 \theta = \frac{\|e_t\|^2}{1 + p^2}$

Solution  $p = -\frac{1}{2c} \left[ (b - a) + \sqrt{(b - a)^2 + 4c^2} \right]$

Alternatively, minimize

$$\phi_q = \|e\|^2 = \|e_x\|^2 \sin^2 \theta = \frac{\|e_x\|^2}{1 + q^2}$$

with solution

$$q = -\frac{1}{2c} \left[ (a - b) + \sqrt{(a - b)^2 + 4c^2} \right]$$

Note  $pq = 1$ .

## TOTAL LEAST SQUARES II

Van Huffel and Vandervalle (1991) define total least squares via SVD analysing the problem

$$\mathbf{C} \begin{bmatrix} p \\ 1 \end{bmatrix} = [Dt_k \quad Dx_k] \begin{bmatrix} p \\ 1 \end{bmatrix} \approx 0$$

We can solve the eigenvalue problem (Porsani et al, 2013)

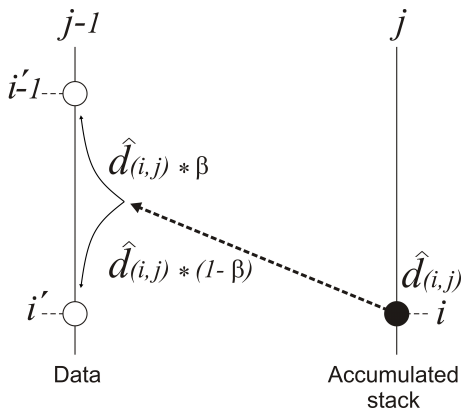
$$\mathbf{C}^T \mathbf{C} \begin{bmatrix} p \\ 1 \end{bmatrix} = \begin{bmatrix} a & c \\ c & b \end{bmatrix} \begin{bmatrix} p \\ 1 \end{bmatrix} = \sigma^2 \begin{bmatrix} p \\ 1 \end{bmatrix}$$

The solution in  $p$  (and  $q$ ) as before, or in a different form

$$p = \frac{-2c}{a - b + \sqrt{(a - b)^2 + 4c^2}} \quad , \quad q = \frac{-2c}{b - a + \sqrt{(b - a)^2 + 4c^2}}$$

## STACKING ALONG LOCAL SLOPE

Started at far offset, hyperbolic extrapolation from near offset to zero offset.



## STACKING ALONG THE NMO VELOCITY SLOPE

Standard travelttime approximation

$$T(x) = \sqrt{T(0)^2 + \frac{x^2}{v_{NMO}^2}}$$

$v_{NMO}(T(0))$  given. For  $(t, x)$  solve

$$t^2 = T(0)^2 + \frac{x^2}{T(0)^2 v_{NMO}^2}$$

for  $v_{NMO}(t, x)$ . Local slope

$$p(t, x) = \frac{x}{t v_{NMO}^2(t, x)}$$

## AUTOMATIC SLOPE STACK

Estimate local slope using total least squares. Check

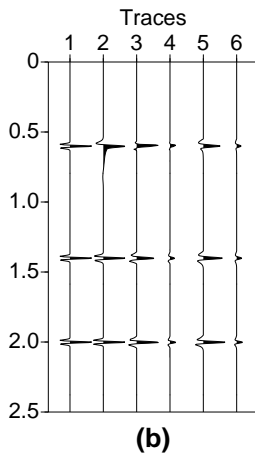
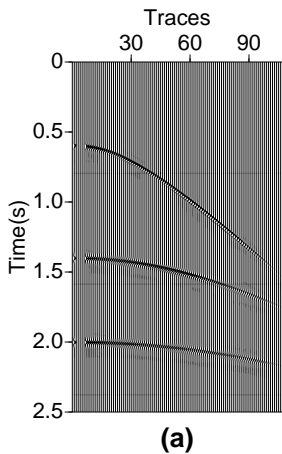
$$\frac{x}{t v_{NMO,max}^2} < p(t, x) < \frac{x}{t v_{NMO,min}^2}$$

If  $p(t, x)$  is outside range, the stack is restarted.

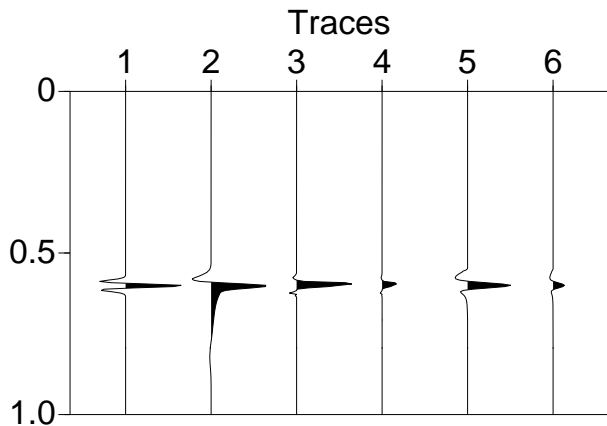
## NUMERICAL EXAMPLES

- 1 - Ideal synthetic data
- 2 - Hess 2D VTI data
- 3 - Deepwater Gulf of Mexico data

## IDEAL SYNTHETIC DATA

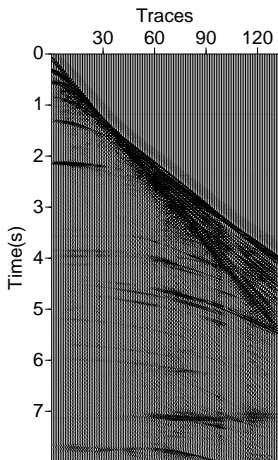


## IDEAL SYNTHETIC DATA

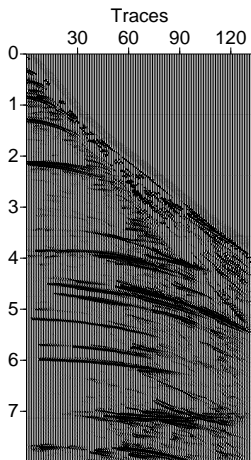




## HESS 2D VTI DATA

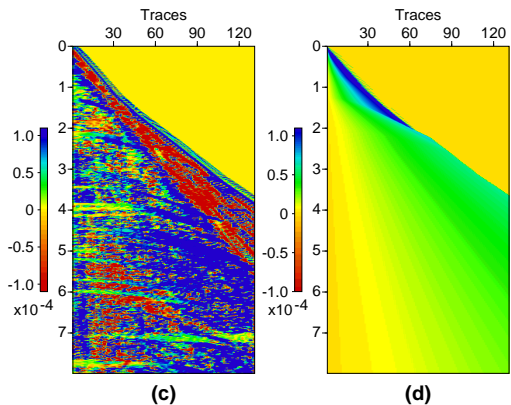


(a)

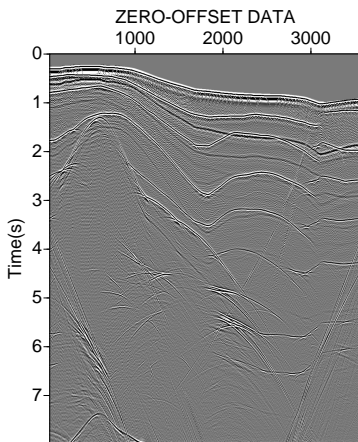


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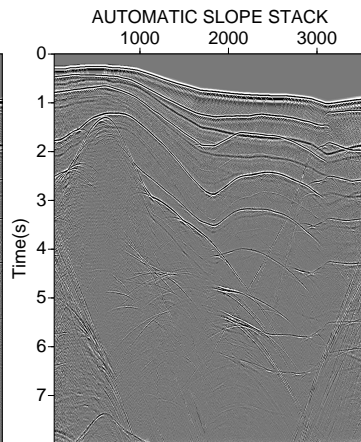
## HESS 2D VTI DATA



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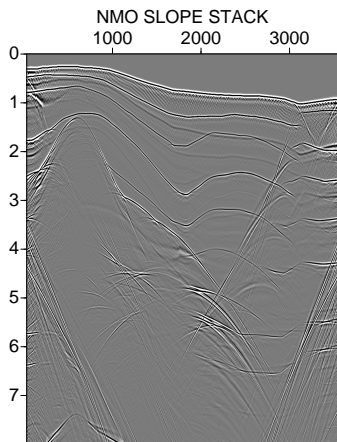


(a)

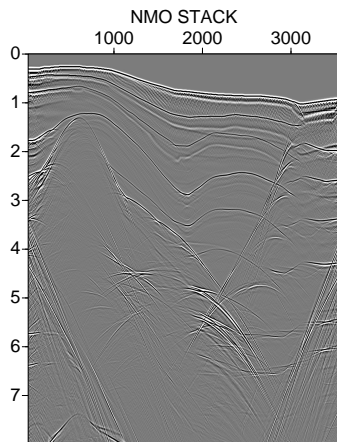


(b)

## HESS 2D VTI DATA

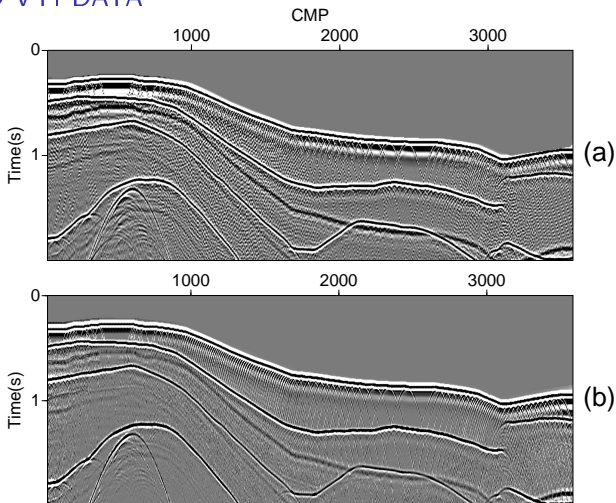


(c)

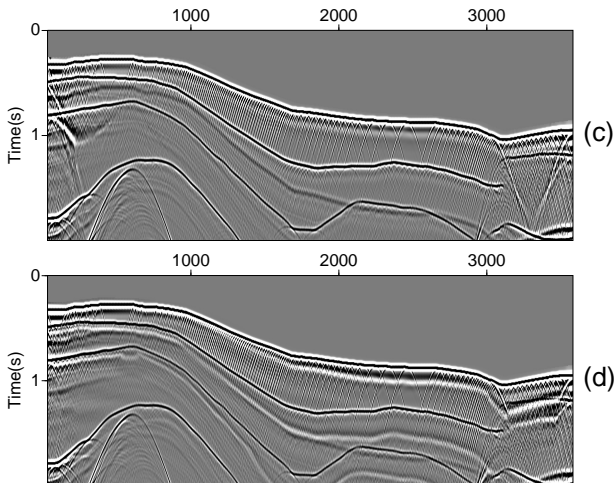


(d)

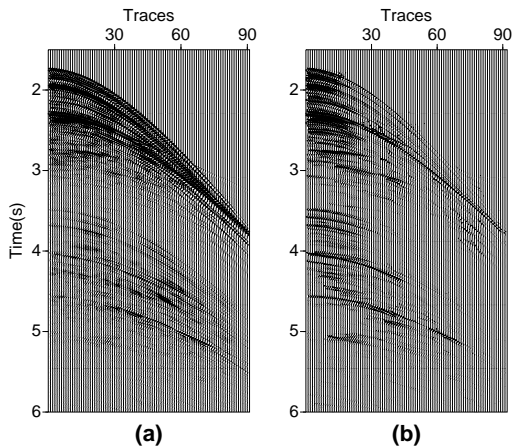
## HESS 2D VTI DATA



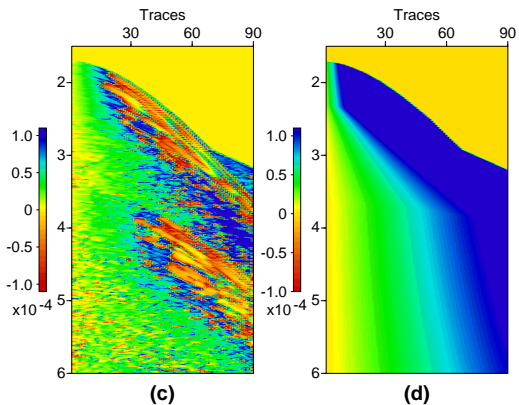
## HESS 2D VTI DATA



## DEEPWATER GULF OF MEXICO DATA

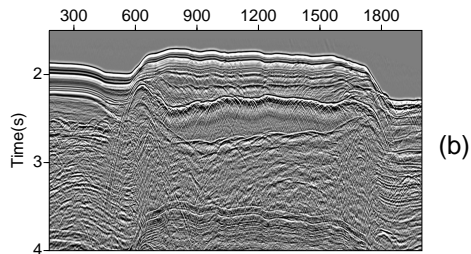
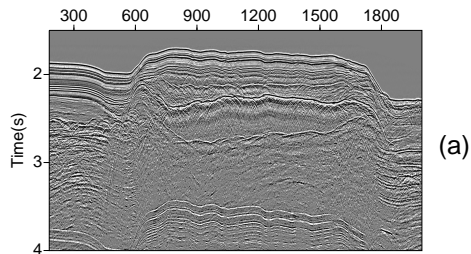


## DEEPWATER GULF OF MEXICO DATA

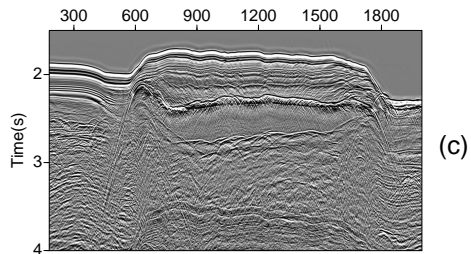
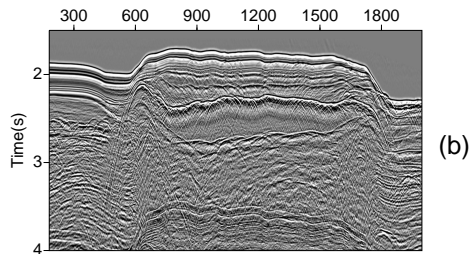




## DEEPWATER GULF OF MEXICO DATA



## DEEPWATER GULF OF MEXICO DATA



## CONCLUSIONS

- ▶ **New estimate of local slope, applications:**
  - Stereotomography
  - Pre-stack time migration
  - Dip filtering
  
- ▶ **New method for slope stack**
  - Fully automatic, no mute
  - Can also use NMO velocities
  
- ▶ **No stretch effect, but only relative amplitudes**

## ACKNOWLEDGEMENTS

- ▶ **Data:** Hess Corporation, WesternGeco
- ▶ **License:** Landmark
- ▶ **Financial support:** INCT-GP/CNPq/MCT, Petrobras, ANP, FINEP, FAPESB, Statoil NFR, Rose Project.

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## LINEAR PROBLEM (Markovsky and Van Huffel, 2007)

Find  $\mathbf{X}$ , such that

$$\mathbf{AX} \approx \mathbf{B}$$

when  $\mathbf{A}$  and  $\mathbf{B}$  are given.

## LEAST SQUARES

$$[\hat{\mathbf{X}}_{LS}, \Delta\mathbf{B}] = \underset{\mathbf{X}, \Delta\mathbf{B}}{\operatorname{argmin}} \|\Delta\mathbf{B}\|_F$$

subject to  $\mathbf{AX} = \mathbf{B} + \Delta\mathbf{B}$ . The Frobenius matrix norm is

$$\|\Delta\mathbf{B}\|_F = \left\{ \sum_i \sum_j |\Delta\mathbf{B}_{i,j}|^2 \right\}^{1/2}$$

Solution

$$\hat{\mathbf{x}}_{LS} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{B}$$

## TOTAL LEAST SQUARES

Consider

$$[\mathbf{A} \quad \mathbf{B}] \begin{bmatrix} \mathbf{X} \\ -\mathbf{I} \end{bmatrix} \approx \mathbf{0}$$

and let  $\mathbf{A} = \hat{\mathbf{A}} + \Delta\mathbf{A}$  and  $\mathbf{B} = \hat{\mathbf{B}} + \Delta\mathbf{B}$ . The total least squares solution

$$[\hat{\mathbf{X}}_{TLS} \quad \Delta\mathbf{A} \quad \Delta\mathbf{B}] = \underset{\mathbf{X}, \Delta\mathbf{A}, \Delta\mathbf{B}}{\operatorname{argmin}} \|\Delta\mathbf{A} | \Delta\mathbf{B}\|_F$$

subject to  $\hat{\mathbf{A}}\hat{\mathbf{X}}_{TLS} = \hat{\mathbf{B}}$ .

## SVD

$$\begin{aligned} \mathbf{C} &= [\mathbf{A} \quad \mathbf{B}] = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \\ &= \mathbf{U} \begin{bmatrix} \mathbf{\Sigma}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{\Sigma}_2 \end{bmatrix} \begin{bmatrix} \mathbf{V}_{11}^T & \mathbf{V}_{21}^T \\ \mathbf{V}_{12}^T & \mathbf{V}_{22}^T \end{bmatrix} \end{aligned}$$

Solution

$$\Delta\mathbf{C} = [\Delta\mathbf{A} \quad \Delta\mathbf{B}] = \mathbf{U} \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{\Sigma}_2 \end{bmatrix} \mathbf{V}^T$$

and

$$\hat{\mathbf{X}}_{TLS} = -\mathbf{V}_{12}\mathbf{V}_{22}^{-1}$$