

## Variable damping in seismic tomography based on ray coverage

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### Summary

In the seismic tomography problem, the subsurface slowness distribution is estimated from the travel-times computed along generally curved rays. For a dense and uniform set of rays, the slowness distribution will be correctly reconstructed. However, for an uneven distribution of rays, the estimated slowness distribution may be influenced by the ray configuration.

For the linear case, the seismic tomography problem can be written as  $A(x - x_0) = (d^{obs} - d^{pred})$  where  $d^{obs}$  and  $d^{pred}$  are the observed and predicted travel-times,  $x$  and  $x_0$  are the true and prior slowness distributions, and  $A$  is the  $(m \times n)$  matrix of partial derivatives  $\partial T_i / \partial u_j$ . Prior estimates of model uncertainty can be used to stabilize the inverse problem (Tarantola, 1987). The stochastic linear inverse can then be written

$$x \approx x_0 + (A^* C_d^{-1} A + C_{x_0}^{-1})^{-1} A^* C_d^{-1} (d^{obs} - d^{pred})$$

where  $C_d$  is the data covariance matrix and  $C_{x_0}$  is the prior model covariance associated with  $x_0$ . Operationally, the diagonal elements of  $C_{x_0}^{-1}$  provide damping of the solution and the off-diagonal elements provide smoothing. The final covariance estimate is then  $C_x = (A^* C_d^{-1} A + C_{x_0}^{-1})^{-1}$ . One might consider using the final covariance matrix  $C_x$  instead of  $C_{x_0}$  in the inverse formula above, however this will lead to an incorrect estimate (Claerbout, 1992).

In addition to the prior uncertainties in the model,  $C_{x_0}$  can also include a discretization correction for variable block sizes (Nolet, 1987). For the case of constant damping and equal ray coverage, the larger blocks will be emphasized at the expense of the smaller blocks. In a very simple example, Nolet (1987) used the underdetermined formulation to invert for two variable length blocks from one travel-time. Using a constant damping this leads to unequal estimates of the slowness parameters in which  $s_1/s_2 = l_1/l_2$ , where  $s_i$  is the slowness and  $l_i$  is the length for each of the two blocks. Incorporating a variable model covariance with diagonal values of  $\sigma_1^2$  and  $\sigma_2^2$  results in the ratio of the slowness estimates of  $s_1/s_2 = \sigma_1^2 l_1 / \sigma_2^2 l_2$ . In order to equalize the slowness estimates from the bias resulting from the unequal block sizes, the diagonal elements of the model covariance matrix can be chosen to be proportional to the inverse of the block lengths. In a 3-D model, the diagonal elements would be proportional to the inverse of the block volumes (Nolet, 1987). For spline parameterizations, the block volumes can be estimated by integration of the individual basis functions.

In addition to the effects of unequal block sizes, unequal ray coverage will affect the inverse solution. One approach to correct for this is to reconfigure the experimental design in such a way as to approximately equalize the ray coverage through the model. Although this is possible in laboratory experiments, in real earth cases this may not be feasible to do. As an alternative, one can specifically construct a model parameterization with unequal cell sizes in such a way as to equalize the ray coverage within each of the cells (Vesnaver, 1996, Curtis and Snieder, 1997).

The effects of unequal ray coverage can also be corrected for by using variable damping. Wang (1993) suggested a variable damping based on the total ray length within a cell. He noted

that the diagonal elements of the matrix  $A^*A$  can be written as  $\sum_{i=1}^m (\partial T_i / \partial u_j)^2$ . For non-

overlapping block parameterization the diagonal values are  $\sum_{i=1}^m (d_{ij})^2$ , where  $d_{ij}$  is the ray length

in the  $j^{th}$  block from the  $i^{th}$  ray. Taking the square-root then results in the Euclidean "length" of vector of ray lengths within a given block. Incorporating the prior covariance, Wang (1993)

chose a variable model damping proportional to  $G = \text{diag} \sqrt{A^* C_{x_0}^{-1} A}$ . Incorporating this, as well as operational damping, he obtained the following inverse formula

$$A_g^{-1} = (A^* C_d^{-1} A + \varepsilon G + \theta^2 D^* D)^{-1} A^* C_d^{-1}$$

where  $\varepsilon > 0$  and  $D$  is a general damping or smoothing operator. Wang (1993) applied this formulation to several synthetic examples using curved-ray refraction tomography, as well as to data from the KRISP90 refraction experiment from Kenya, and found that the addition of the  $G$  term reduced artifacts of the inversion results due to ray concentrations.

These results can be extended by using the general square-root operator and the SVD decomposition. We first look at the inverse operator  $(A^* A + \varepsilon \text{sqrt}(A^* A))^{-1} A^*$ . The SVD

decomposition of  $A$  can be written as  $A = (U_p U_0) \begin{pmatrix} \Lambda_p & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} V_p^* \\ V_0^* \end{pmatrix}$  where  $U_p$  and  $U_0$  span

the range-space and orthogonal range-space,  $V_0$  and  $V_p$  span the null-space and orthogonal null-space, and  $\Lambda_p$  are the  $p$  nonzero singular values  $\lambda_i$  (Lanczos, 1961). Assuming that the rank  $p$  is equal to  $n$ , the size of the model space, then the inverse operator above can be written as

$A_{g1}^{-1} = V_p \begin{pmatrix} \lambda_i \\ \lambda_i^2 + \varepsilon \lambda_i \end{pmatrix} U_p^* = V_p \begin{pmatrix} 1 \\ \lambda_i + \varepsilon \end{pmatrix} U_p^*$ . In contrast, the simple, damped least squares

solution can be written  $A_{dls}^{-1} = (A^* A + \varepsilon^2 I)^{-1} A^* = V_p \begin{pmatrix} \lambda_i \\ \lambda_i^2 + \varepsilon^2 \end{pmatrix} U_p^*$ . A comparison of these

formulas shows that the small singular values of  $A_{dls}^{-1}$  go to zero for  $\lambda_i < \varepsilon$ , whereas the small singular values of  $A_{g1}^{-1}$  go to  $1/\varepsilon$ . Thus for  $A_{g1}^{-1}$ , the small singular values are weighted more

heavily than for the damped least squares solution. In the tomography problem, the small singular values correspond to block with less ray coverage.

Although the inverse solution  $A_{g1}^{-1}$  is nonsingular when constructed using the SVD decomposition, by using a least squares formulation the inverse will be singular when there are zero singular values, or when blocks with no rays occur. Using least squares, this can be avoided by using an additional small damping as was done by Wang (1993). Using a simple damping

this can be written  $A_{g2}^{-1} = (A^*A + \varepsilon \text{sqrt}(A^*A) + \vartheta^2 I)^{-1} A^* = V_p \left( \frac{\lambda_i}{\lambda_i^2 + \varepsilon \lambda_i + \vartheta^2} \right) U_p^*$

where  $\varepsilon > \vartheta$ . The additional small damping eliminates the very small and zero singular values in the least squares formulation.

Finally, the zero singular value components can be incorporated into the solution by damping the SVD formulation such that  $A_{g3}^{-1} = (V_p \ V_\varepsilon) \begin{pmatrix} 1/(\lambda_i + \varepsilon) & 0 \\ 0 & 1/\varepsilon \end{pmatrix} \begin{pmatrix} U_p^* \\ U_\varepsilon^* \end{pmatrix}$  where  $U_\varepsilon$  and  $V_\varepsilon$  are the augmented data and model vectors associated with zero singular values modified to  $1/\varepsilon$ . However, it's as yet unclear whether this is physically reasonable. By truncating the  $1/\varepsilon$  singular values, the  $A_{g3}^{-1}$  inverse reduces to the  $A_{g1}^{-1}$  inverse above.

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