Estimation of *P-SV* residual statics by stack-power optimization

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ABSTRACT

The residual-statics problem for mode-converted (*P-SV*) seismic data is investigated, using a method that optimizes the power of the trace-mixed stack. We have tried both the simulated-annealing and iterative-improvement methods. So far, our results using iterative improvement have been better, and have required considerably less computer time. In our algorithm, the maximum shot and receiver terms are constained independently, to allow for *S*-wave receiver statics that are much larger than the corresponding *P*-wave source statics.

We have tested this methodology using a *P-SV* dataset from the Slave Lake area in northern Alberta. Attempts to obtain a residual-statics solution using a conventional (Gauss-Seidel) residual-statics algorithm have only been partially successful, due to the unusually large receiver-static term. By solving for receiver statics only, the trace-mixed stack-power optimization method gives a better overall stack, with more plausible source and receiver statics.

INTRODUCTION

Processing of converted-wave seismic data requires certain special considerations, such as common-conversion-point binning techniques (Eaton et al., 1990) and a modified moveout formula (Slotboom, 1990). However, from the processor's perspective, the most problematic step is often the determination of large residual *S*-wave statics for the receiver stations. Unlike *P*-waves, the velocity of *S*-waves are virtually unaffected by near-surface fluctuations in the water table (Figure 1). Hence, the *P*-wave and *S*-wave static solutions are mutually uncorrelated, and it is not generally feasible to approximate the *S*-wave statics by simply scaling known *P*-wave static values (Lawton, 1991). Nevertheless, the statics problem for converted-wave recordings is still somewhat simpler than for the pure *S*-wave case (*SV-SV* or *SH-SH*), because the source statics from the corresponding vertical-component (ie. *P-P*) data are usually available.

Several approaches to the *P-SV* statics problem have been reported previously. In general, the *S*-wave statics have been sufficiently large that manual picking of receiver statics and/or *S*-

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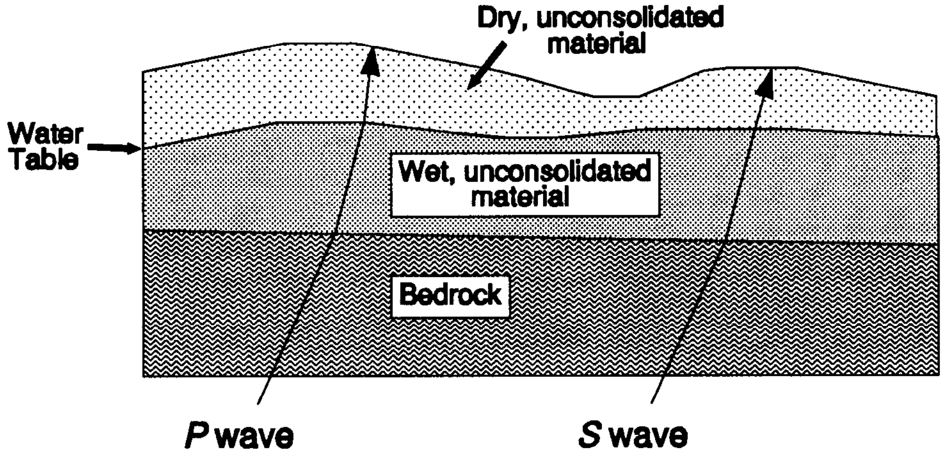

FIG. 1. P-wave velocity is affected by the presence of the water table, whereas S-wave velocities are not. Thus, P-wave and S-wave statics are usually uncorrelated.

wave refraction methods have been deemed necessary (Harrison, 1989; Schafer, 1990; Li et al., 1990). Both methods, however, are very laborious and time consuming. Refraction methods also suffer from certain other practical limitations. For example, it may be difficult to unambiguously identify refraction modes (eg. *PPS, PSS, SPS, SSS* etc.), or to make the picks with sufficient accuracy in the presence of noise.

Recently, new techniques for estimating surface-consistent residual statics have been developed, based on the principle of maximizing the total stacking power (Ronen and Claerbout, 1985; Rothman, 1985; 1986; Dahl-Jensen, 1989). However, we are not aware of any published applications of this methodology to converted-wave data. Ronen and Claerbout (1985) use an iterative-improvement algorithm to optimize the stacking power. This technique is very similar to popular gradient-descent methods for nonlinear inverse problems (Adby and Dempster, 1974), and converges very quickly, but is prone to entrapment in a local minimum of the objective function. Rather than successively restacking the data to compute the stacking power, Ronen and Claerbout (1985) employ a more economical supertrace crosscorrelation technique. Rothman (1985; 1986) uses a similar approach, but utilizes simulated annealing as an optimization method. Simulated annealing is more likely than iterative improvement to converge to the global minimum, but at the expense of a great deal of computer time.

Vasudevan et al. (1991) point out that the stack power, as defined by Ronen and Claerbout (1985), does not account for trace-to-trace coherence of the stack. Vasudevan et al.

abandoned the supertrace approach altogether, in favour of an optimization function defined by the multiplication of two adjacent CDP-stacked traces. We chose to retain the supertrace approach, because of its efficiency and its application to the implementation of simulated annealing using the heat-bath method (Rothman,1986). To incorporate a measure of trace-to-trace coherence into the objective function, we modify the stack-power approach so that the power of the running-mix of the stack is optimized, instead of the normal CDP stack.

The aim of this paper is to introduce a modified stack-power optimization method for computing residual statics, and to apply this algorithm to a *P-SV* dataset. We begin with a review of the stack-power optimizaton approach to surface-consistent statics estimation. Next, we describe our modifications to the supertrace crosscorrelation technique, and the implementation of this approach to simulated annealing by the heat bath method. We then apply these algorithms to a *P-SV* dataset from the Slave Lake area in northern Alberta.

METHOD

Review of previous linear methods

According to the surface-consistent hypothesis (Taner et al., 1974, Wiggins et al., 1976), the total static, t_{ij}, for the trace corresponding to the *ith* source and the *jth* receiver may be written as the sum of four terms

$$t_{ij} = s_i + r_j + g_k + m_k x_{ij}^2 \quad , \tag{1}$$

where s_i is the source term, r_j is the receiver term, g_k is the geologic structure term, m_k is the NMO term and x_{ij} is the source-receiver offset (residual moveout is normally modeled using a parabolic approximation, for simplicity). g_k and m_k are assumed to be subsurface consistent; for *P-P* recordings, the index k is taken to be the CMP number. For *P-SV* data, some suitable approximation for the common conversion point (CCP) should be used for k.

Ronen and Claerbout (1985) suggested that an optimal set of static terms could be determined by maximizing the total stacking power,

$$E = \sum_k \sum_t u_k^2(t) \quad . \tag{2}$$

where $\mathbf{u}_k$ is the stacked trace at position k. Starting from an initial guess, the statics are calculated by iterative improvement. The algorithm visits each i, j and k successively, and determines the static value that will maximize the total stacking power, keeping all of the other parameters fixed. One iteration consists of a single pass through every shot location, receiver station and CMP or

CCP. Note that the statics computed in this way are unable to resolve wavenumbers longer than the spread length (Wiggins et al., 1976). For example, adding a constant value to any of the terms has no effect on the total stacking power, E.

Modified stacking power

Our initial tests of this approach indicated that visually undesirable results can sometimes be obtained by maximizing E, as defined in equation (2). These solutions correspond to local minima of the objective function, and the algorithm has difficulty discriminating against them because they have stacking power that is close to the global maximum value. These undesirable solutions are characterized by an "aliased" appearance, with very poor trace-to-trace coherence (see Figure 5). This prompted us to test the use of a running-mix on the stacked data, and modify the objective function accordingly:

$$E' = \sum_k \sum_t \{\sum_{l=-n}^{n} u_{k+l}(t)\}^2 \quad . \tag{3}$$

In equation (3), n represents the number of adjacent traces to sum, ie.$(N_m-1)/2$, where N_m is the number of traces in the mix. The results of using equation (3) rather than (2) suggest that even a small value of N_m, such as 3, significantly improves the convergence of the algorithm to a more desireable minimum.

Modified supertraces

Ronen and Claerbout (1985) showed that maximization of E could be accomplished economically using a crosscorrelation technique. To explain their technique, we denote by N_s the difference k_{max} - k_{min} between the maximum and minimum CMP (or CCP) contained in a given source gather (and similarly for N_r). The remainder of the stack is not changed by any choice of static for the given source position. Consider the partial stack formed by summing all of the traces between k_{min} and k_{max}, but excluding the traces from the given source. The concatenation of all of the traces (with blocks of zeros separating them) from the partial stack forms supertrace 1 ($\tilde{\mathbf{u}}^{(1)}$), and the concatenation of the traces from the given shot forms supertrace 2 ($\tilde{\mathbf{u}}^{(2)}$), (traces F and G in Ronen and Claerbout (1985). The sum of supertrace 1 and supertrace 2 constructed in this manner results in a single trace that is the same as the concatenation of the fully stacked traces between k_{min} and k_{max}, separated by blocks of zeros. The total power in this portion of the stack as a function of the source static (Δt) may be written

$$
\begin{aligned}
E(\Delta t) &= \sum_{k=k_{min}}^{k_{max}} \sum_{t} (\bar{u}_k^{(1)}(t-\Delta t) + \bar{u}_k^{(2)}(t))^2 \\
&= \sum_{k=k_{min}}^{k_{max}} \sum_{t} [\bar{u}_k^{(1)}(t-\Delta t)]^2 + [\bar{u}_k^{(2)}(t)]^2 \; + \; 2\sum_{k=k_{min}}^{k_{max}} \sum_{t} \bar{u}_k^{(1)}(t-\Delta t)\bar{u}_k^{(2)}(t) \quad .
\end{aligned}
\tag{4}
$$

Equation (4) states that $E(\Delta t)$ is equal to the sum of the power in each supertrace (a constant) + twice the crosscorrelation of the two traces. Thus, the lag Δt corresponding to the crosscorrelation maximum for the two supertraces also represents the static that will maximize E.

Exactly the same argument can be used to design a crosscorrelation technique suitable for trace-mixed data. The method is depicted schematically in Figure 2. In this case, a running mix is applied to the partial stacked traces as well as the traces from the given source or receiver, prior to concatentation to form mixed supertraces (or equivalently, the supertraces are formed first, and then mixed as shown in Figure 2). To distinguish this method from Ronen and Claerbout's (1985) approach, we call these super-duper traces. The length of each super-duper trace is N_m-1 regular traces longer than the corresponding supertrace. For each iteration, the modified iterative-improvement algorithm then consists of:

1) visiting each source and receiver location;
2) forming the super-duper traces;
3) cross-correlating the super-duper traces, and picking the maximum;
4) applying the new source/receiver static to the data.

If desired, the additional surface-consistent static terms (g_k and m_k) can be estimated using conventional techniques.

Simulated annealing

Theoretical discussions of the simulated annealing method are found in Kirkpatrick et al. (1983), Geman and Geman (1984), and Rothman (1985). Here, following Rothman (1986), we adapt the crosscorrelation technique described above to the simulated annealing technique known as the heat-bath algorithm. In essence, the degree of randomness incorporated into the simulated annealing method provides a means of escaping from local minima for nonlinear problems, but is faster than inversion by an exhaustive search of the model space (e.g. velocity analysis), or a truly random search. The heat-bath algorithm is a more efficient implementation of simulated annealing than other approaches, such as the Metropolis algorithm (Rothman, 1985; Vasudevan et al., 1991).

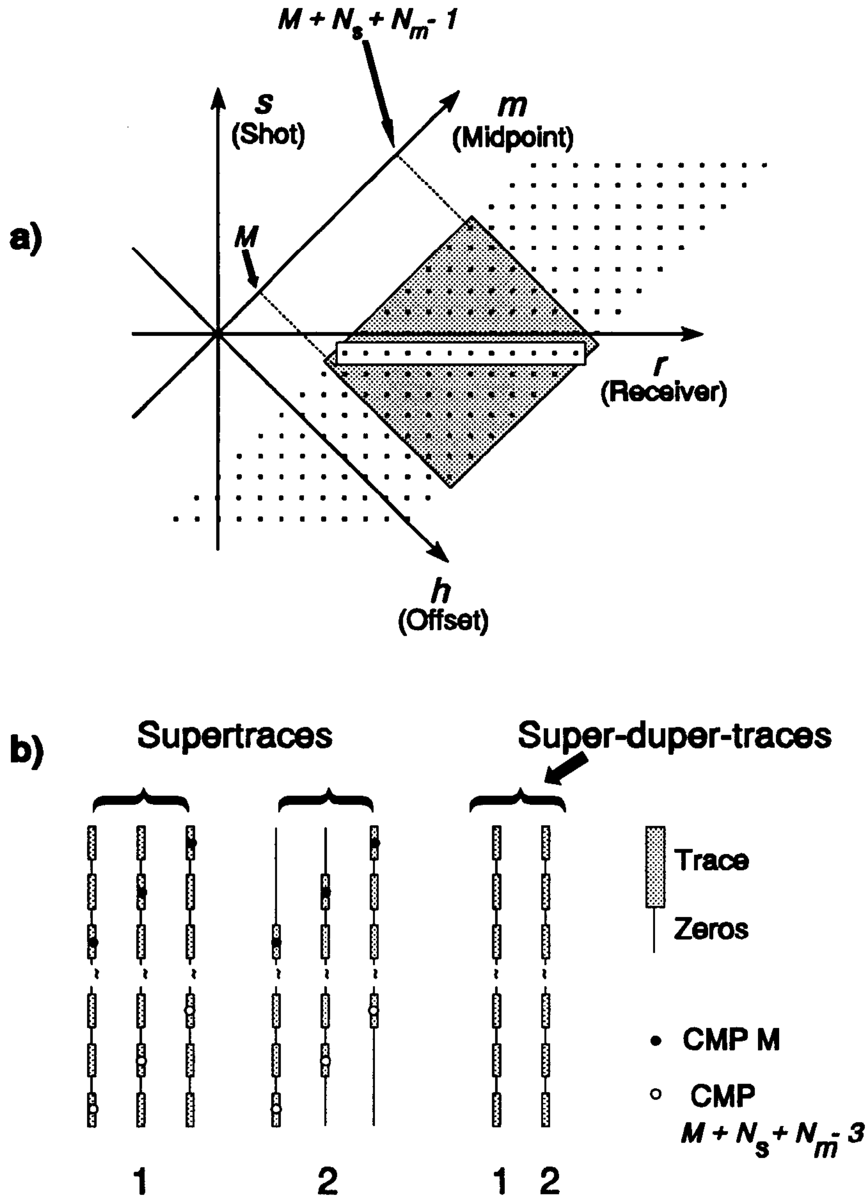

FIG. 2. a) Stacking chart showing portion of the seismic survey used to construct super-duper traces, for a 3-trace mix. b) Data organization for the super-duper traces. Each super-duper trace can be considered as the mix of three supertraces, formed by concatenation of original data traces (Ronen and Claerbout, 1985). The sum of the two super-duper traces produces a single trace that is the same as the concatenation of traces from the running mix of the stack. This Figure shows the method for CMP subsurface consistency. The same method is used for CCP consistency, but with minor modifications to the stacking chart (see Eaton and Lawton, 1991).

The heat-bath method transforms cross-correlation functions to a normlized probability distribution. First, the normalized cross-correlation function, ϕ is computed using

$$\tilde{\phi}(\Delta t) = A^{-1/2}\phi(\Delta t) \quad , \tag{5}$$

where A is a normalization factor given by

$$A = \{\sum_{k=k_{min}}^{k_{max}} \sum_{t} [\bar{u}_k^{(1)}(t)]^2\} \cdot \{\sum_{k=k_{min}}^{k_{max}} \sum_{t} [\bar{u}_k^{(2)}(t)]^2\} \quad , \tag{6}$$

and ϕ is the cross-correlation function defined by equation (4). The algorithm is similar to the iterative-improvement algorithm, except that instead of always picking the maximum of the cross-correlation function, a new static value, τ, is computed by randomly selecting a value from the Gibbs distribution

$$P(\tau = \Delta t) = \frac{e^{\tilde{\phi}/T}}{\int_{-\infty}^{\infty} e^{\tilde{\phi}/T}} \quad . \tag{7}$$

For reasons that are discussed below, the control parameter T in equation (7) has a close physical analogy with the temperature (scaled by Boltzmann's constant) of an ideal fluid in thermal equilibrium. Very large values of T cause the prior probablility distribution, $P(\tau = \Delta t)$ to be nearly uniform, regardless of the nature of the cross correlation function. Conversely, for a temperature of zero, $P(\tau = \Delta t)$ reduces to a delta function, spiking at the maximum cross-correlation lag. Thus the random-search and iterative-improvement algorithms are both special cases of the simulated annealing method. At some intermediate value for T, the behaviour of the algorithm shifts from a nearly linear to a nearly random optimization technique. Running close to the temperature where this transition occurs (the *critical* temperature), the algorithm is more likely to select static values that will improve the stacking power, but retains the ability to escape from local minima caused by cycle skipping.

The Gibbs distribution arises in the study of large aggregates of atoms in thermal equilibrium, and its choice as the form of the prior probability function for the static values is deliberate. As a consequence of this choice, the extensive body of theoretical knowledge in the field statistical mechanics can be brought to bear on the present problem. For example, convergence of the algorithm can be demonstrated analytically (Geman and Geman, 1984; Rothman, 1986). By analogy with the thermodynamic process of crystal formation, the simulated annealing method works best when the system is cooled slowly through the critical temperature.

Unfortunately, we have found that determination of the critical temperature is often difficult and time consuming. Furthermore, the behaviour of the algorithm seems to be quite sensitive to the nature of the cooling schedule used. Methods for accurately predicting the critical temperture (e.g. Frazer and Basu (1990)) and obtaining a practical understanding of how to formulate an optimal cooling schedule (Paulson, 1986) are important considerations for this approach.

REAL DATA EXAMPLE

We use the radial component of Slave Lake line EUE001 from northern Alberta to test the stack-power optimization methods described above. This is a good line to test statics algorithms because it generally has good quality signal, but is contaminated with large statics (Schafer, 1990). The radial component of the data has been re-processed and the brute CMP stack of the radial section is shown in Figure 3a. Elevation statics and refraction plus residual shot statics derived from the processing of the vertical component have been applied, but there are still large statics remaining. The statics problems are clearly evident in the common-receiver stack in Figure 3b and the common-shot stack in Figure 3c. The poor continuity of the shot stack was surprising at first because we expected the shot statics to be largely resolved by the vertical component processing.

Initially we did not know whether the poor continuity of the shot stack was caused by the large residual receiver statics that still remain in the data, or by shot statics that were unresolved by the processing of the vertical component of the data. After extensive testing with the stack-power optimization methods, we found that the best shot stacks were obtained without solving for shot statics. Therefore, it seems that the poor shot stack in Figure3c is not indicative of the existence of large unresolved shot statics, but rather the effect of large unresolved receiver statics on the shot stack.

The first attempt to resolve the statics for this line used a conventional residual statics program based on a four component surface-consistent Gauss-Seidel decomposition. The result from this program illustrates very well the problems encountered with solving for statics for P-SV data. Like most programs of this nature, it is not designed to search for larger receiver statics than shot statics, or to search for receiver statics only, as P-SV statics require. The program was allowed to solve for a maximum of ±40 ms statics, which is split between the shot and receiver terms in whichever way gives the best surface-consistent result. This allows for a maximum shift of 80 ms between adjacent traces. This magnitude of static shift was considered to be the minimum required to resolve the statics present in the receiver stack (Figure 3a). Figure 4a shows the resulting CMP stack. The Gauss-Seidel method was able to improve the left-hand side of the line, but had no success with the more difficult right-hand side of the line. The receiver stack in Figure 4b shows considerable improvement on the left-hand side of the line, but cycle-skipping is evident. The right-hand side shows no improvement over the brute stack. The shot stack in

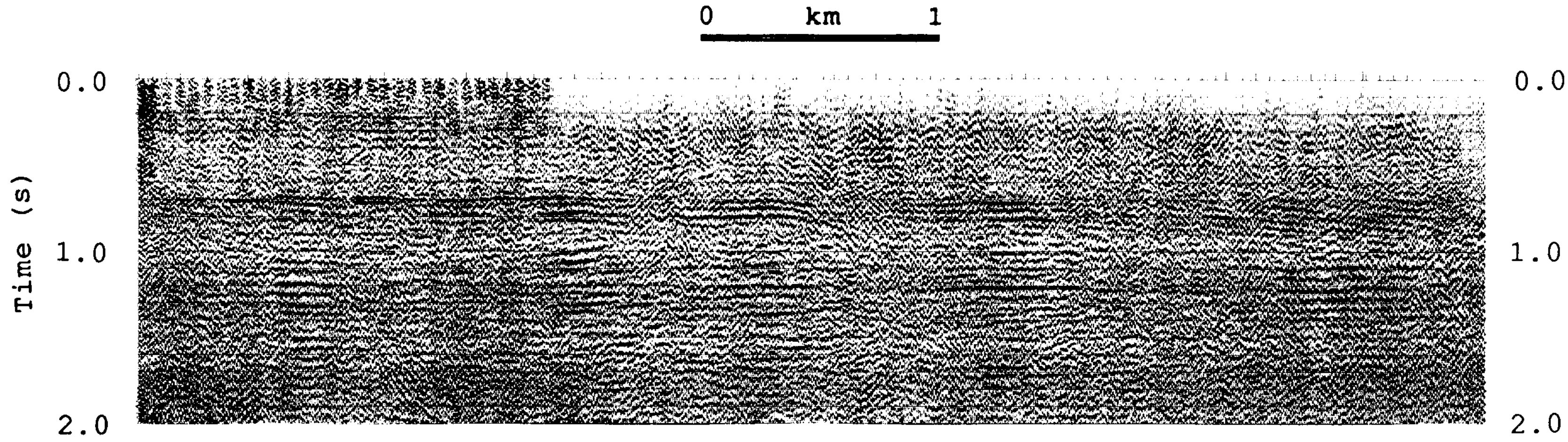

Fig. 3a. Brute CMP stack section of the radial (P-SV) component from Line EUE001, Slave Lake, northern Alberta.

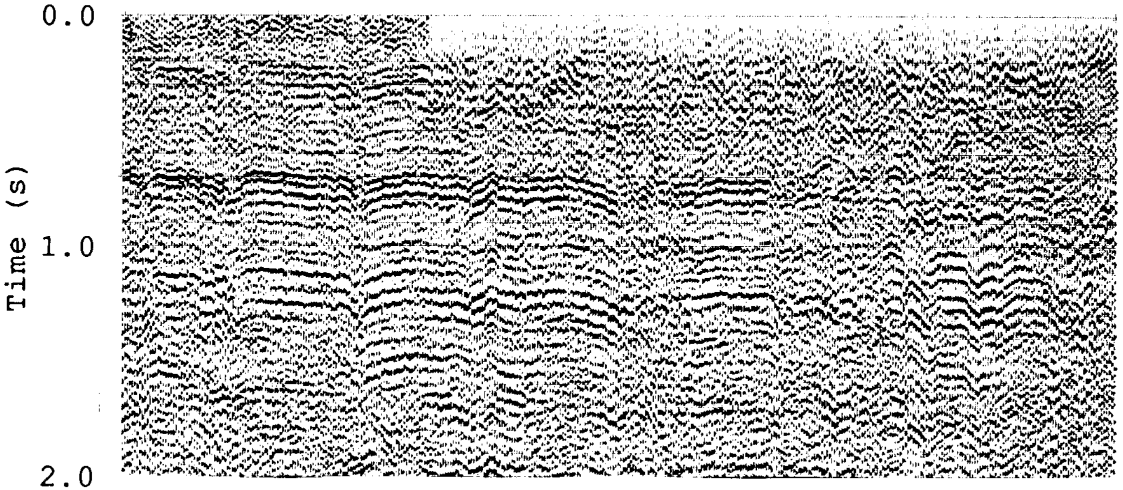

Fig. 3b. Brute common-receiver stack.

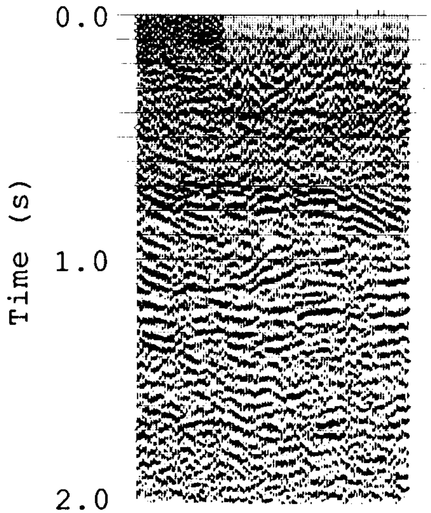

Fig. 3c. Brute common-source stack.

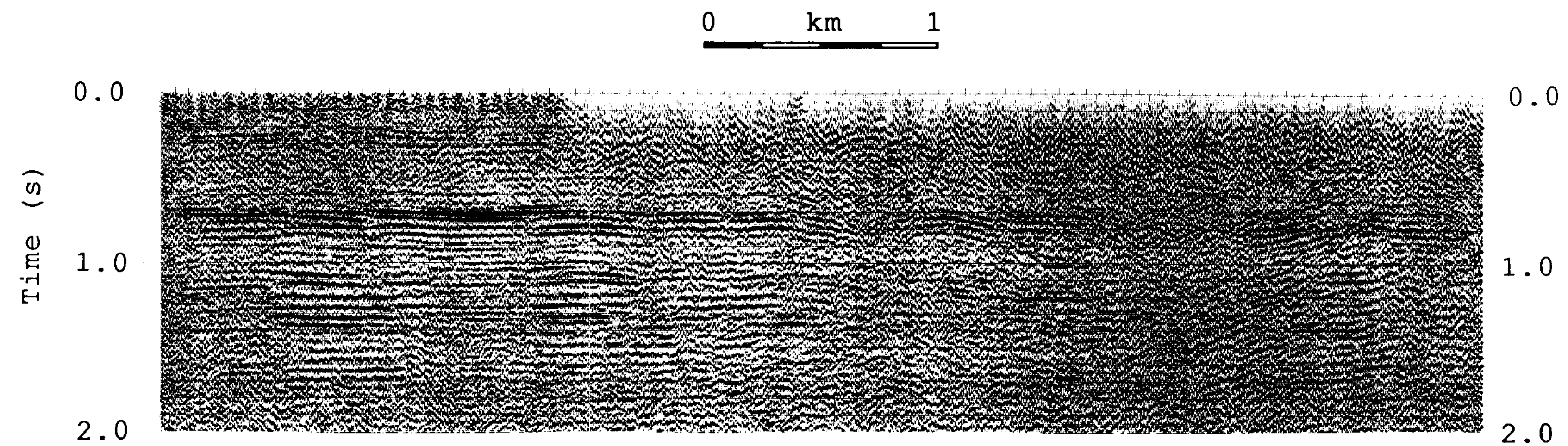

Fig. 4a. Stack section with residual statics computed by conventional Gauss-Seidel algorithm.

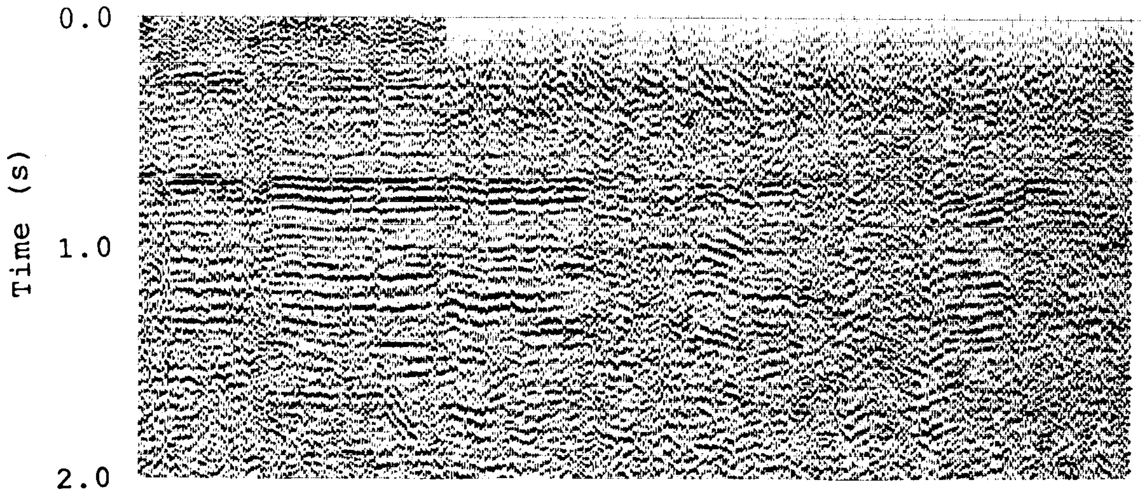

Fig. 4b. Common-receiver stack with Gauss-Seidel statics.

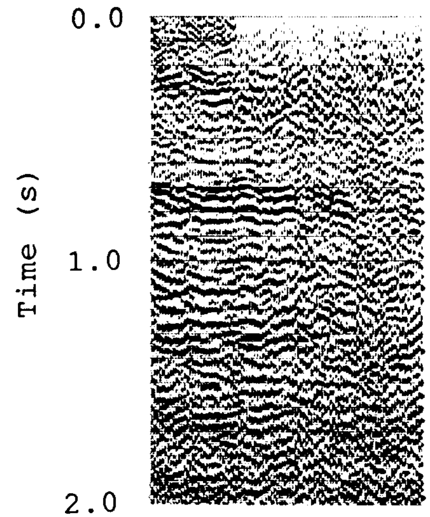

Fig. 4c. Common-shot stack with Gauss-Seidel statics.

Figure 4c shows some improvement on the left-hand side of the line. However, the shot statics obtained by the Gauss-Seidel program were often larger than 20 ms. We have reason to believe that no large shot statics still exist in the data, because the vertical component statics were well resolved. We therefore believe that some of the improvement in the receiver stack has been obtained at the expense of forcing errors into the shot terms. The static busts in the CMP stack therefore are probably due to erroneous shot statics.

Because of the inability to independently set the maximum size of the shotand receiver statics in the Gauss-Seidel residual statics program, further tests were carried out by the method of stack-power optimization. This is not to say that the Gauss-Seidel method could not be adapted to allow this desired flexibility -- it easily could. However, the main purpose of this study is to evaluate the stack-power optimization method. This program was written with the *P-SV* statics problem specifically in mind.

To prepare for testing with stack-power optimization, we first filtered the data back to 45 Hz. and resampled from 2 ms to 8 ms. The filtering was done because the signal was only considered reliable up to that range. The data were resampled partly to speed up the computer runs and partly because statics smaller than 8 ms were not considered important in our initial attempts to resolve the large statics remaining in the receiver term. It is understood that further statics runs to fine-tune the results with the original 2 ms data would be required once the gross statics have been resolved.

Our first attempt at using stack-power optimization to resolve the receiver statics used the method exactly as it is described by Ronen and Claerbout (1985). The resulting CMP stack appears to have converged to an undesireable local mininum, as shown in Figure 5, and is even worse than the brute stack. Notice the aliased appearance of some portions of the stack.

We next tried using equation (3) with the number of traces used in the running-mix set to 3. The resulting CMP stack, shown in Figure 6a, is dramatically better than Figure 5, and also considerably better than the brute stack. Obviously the modification to the algorithm to search for the best running-mixed stack-power is very important to the success of the method. A test that increased the amount of mixing from 3 to 7 traces did not yield better results, but used more computer time. It therefore appears that a value of 3 is all that is required to constrain the CMP variations to be smooth.

Despite the improvement to the CMP stack, the receiver stack in Figure 6b shows obvious problems. Several static busts can be seen near the middle of the line. On the right-hand side of the line the statics have been improved, but there probably is a static bust between this part of the line and the rest. The zone of poor data between the two well resolved parts of the line makes it difficult to track horizons from one end of the line to the other. It may be too much to expect any statics algorithm to not produce a bust through this region. These results were obtained by setting the maximum receiver static to ±104 ms, which is probably larger than necessary.

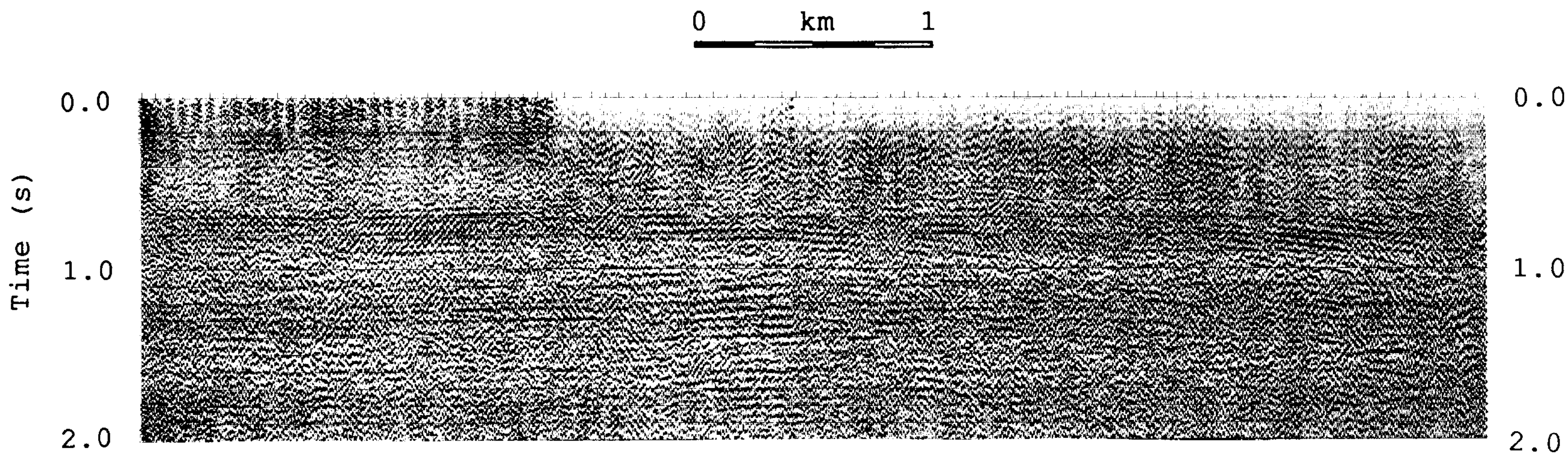

Fig. 5. Stack section with residual receiver statics computed by stack-power optimization without trace mixing.

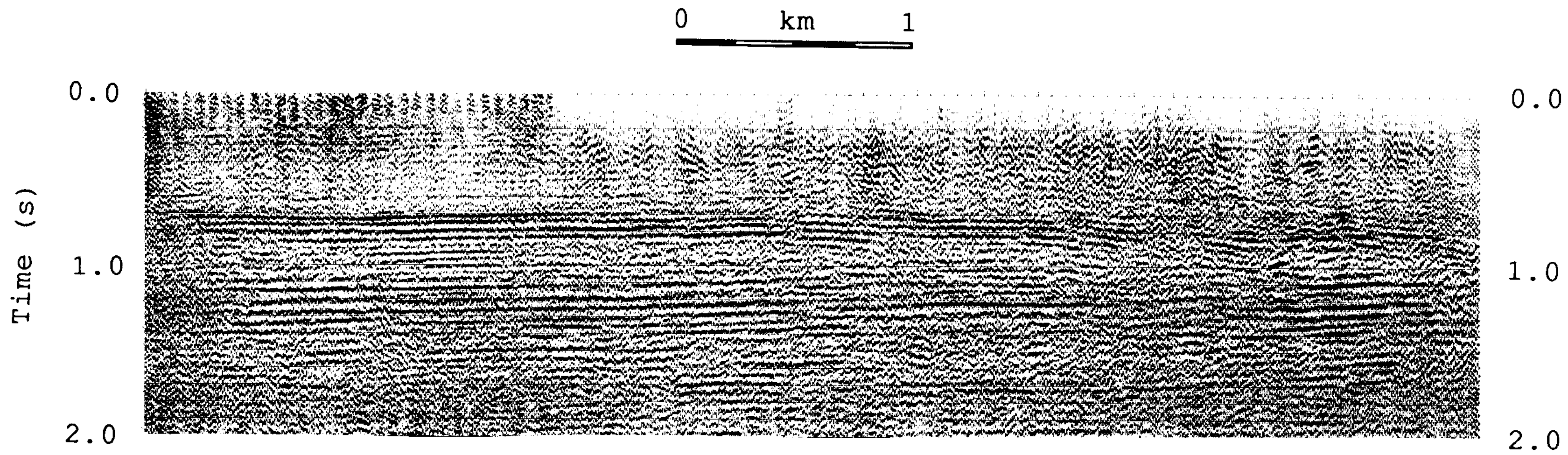

Fig. 6a. Stack section with residual receiver statics computed by stack-power optimization with trace mixing.

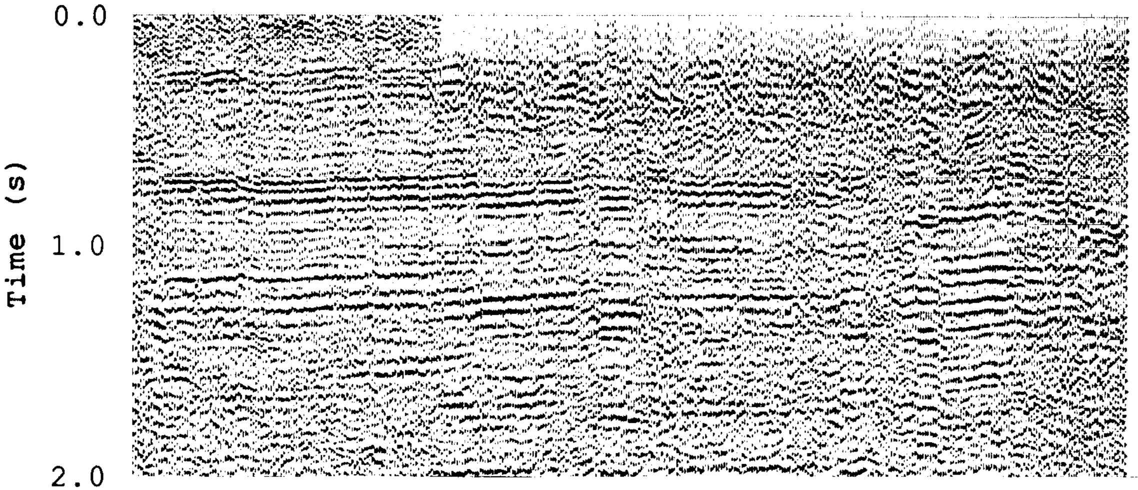

Fig. 6b. Common-receiver stack with stack-power statics.

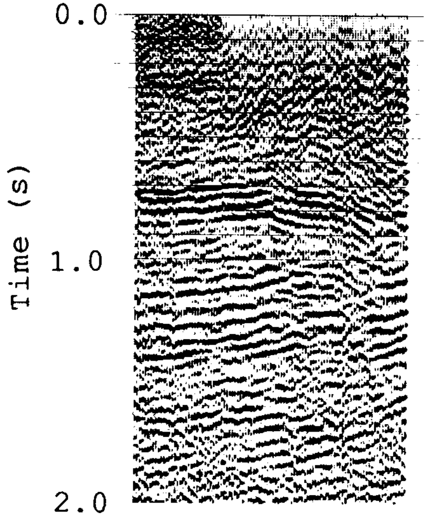

Fig. 6c. Common-shot stack with stack-power statics.

However, tests with smaller maximum statics produced very similar results. Shot statics were constrained to be zero. The shot stack in Figure 6c shows a large improvement over Figure 3c, especially on the left-hand side of the line, even though only receiver statics have been modified.

The results thus far indicate that stack-power optimization is capable of resolving much of the statics problems in this data, but that the results are prone to static busts along the line. It would be a relatively straightforward procedure to fix these static busts by hand, but it would certainly be better if the program did not produce them in the first place. Several methods of modifying the stack-power optimization method have been suggested to solve the cycle-skipping problem. We examine some of these next.

We first tried the simulated annealing method of Rothman (1985; 1986). We have not done as much testing as we would like, but we can summarize ourresults thus far as being disappointing. To date, our successes with this method have been confined to small-scale synthetic datasets. We may not be using a correct cooling schedule, because our results are quite independent of the number of iterations that are used once the system has been cooled to our chosen critical temperature. The results in Figure 7 were obtained after only 150 iterations, which is very short for this method. Obviously these results still suffer from cycle-skipping problems, so the faster method of iterative improvement is preferred at this time. Although it may be that a slower cooling schedule is required to get a better result, the enormous amounts of computer time required for this method makes it unattractive at this time.

Dahl-Jensen (1989) makes claims that static busts with stack-power optimization can be avoided with two variations to the Ronen and Claerbout (1985) method. His first suggested variation is to solve for the receiver statics in a random order within each iteration, rather than solving for them sequentially from one end of the line to the other. Although Dahl-Jensen did not provide any firm reasons for why this would help, it may be that the random solution order would prevent the solution from going off track systematically, which is what occurs at a cycle skip. Figure 8 shows the CMP stack obtained by solving for receiver statics in a random order within each iteration as suggested by Dahl-Jensen. Unfortunately, static busts still remain. Dahl-Jensen also suggested that constraining the size of static jumps between adjacent receivers would reduce the cycle-skipping problem. The original receiver stack, Figure 3b, indicates jumps at least as big as 32 ms between receivers are required to resolve the receiver statics correctly, so this was used as the maximum allowed difference between adjacent receivers in obtaining the CMP stack in Figure 9. Since the dominant period of the data is about 40 ms, one might expect a 32 ms constraint to be sufficient to remove the static busts. Paradoxically, static busts larger than 32 ms still exist in Figure 9. A close examination of the receiver stack shows that in at least two places, 64 ms busts have occurred over two traces, so the 32 ms constraint is still not sufficient to prevent busts.

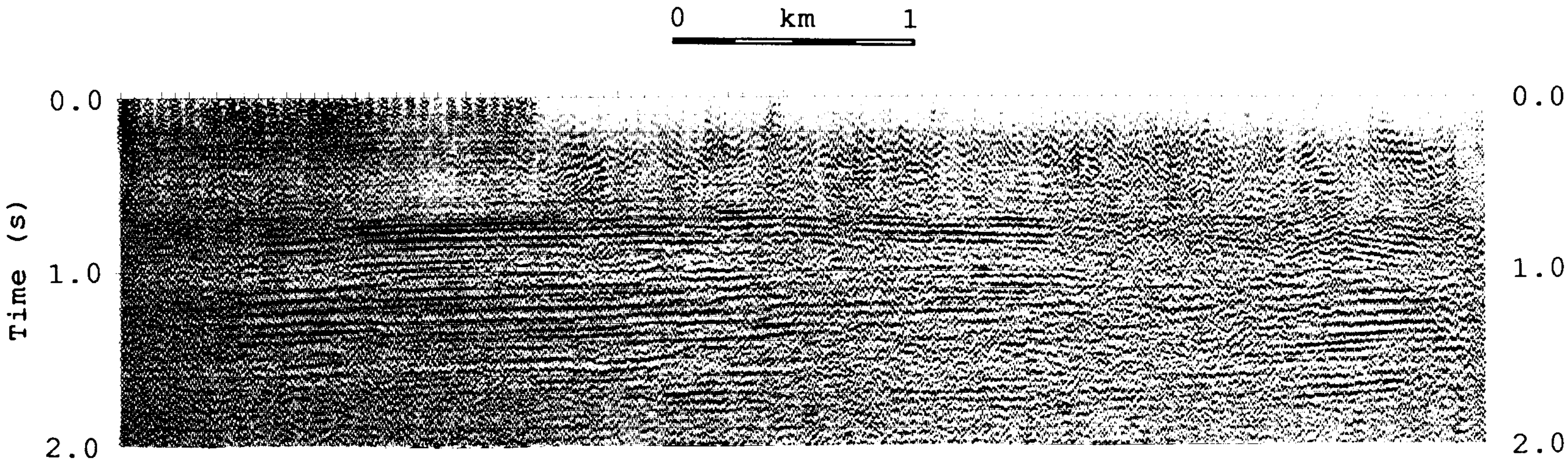

Fig. 7a. Stack section with residual receiver statics computed by simulated annealing.

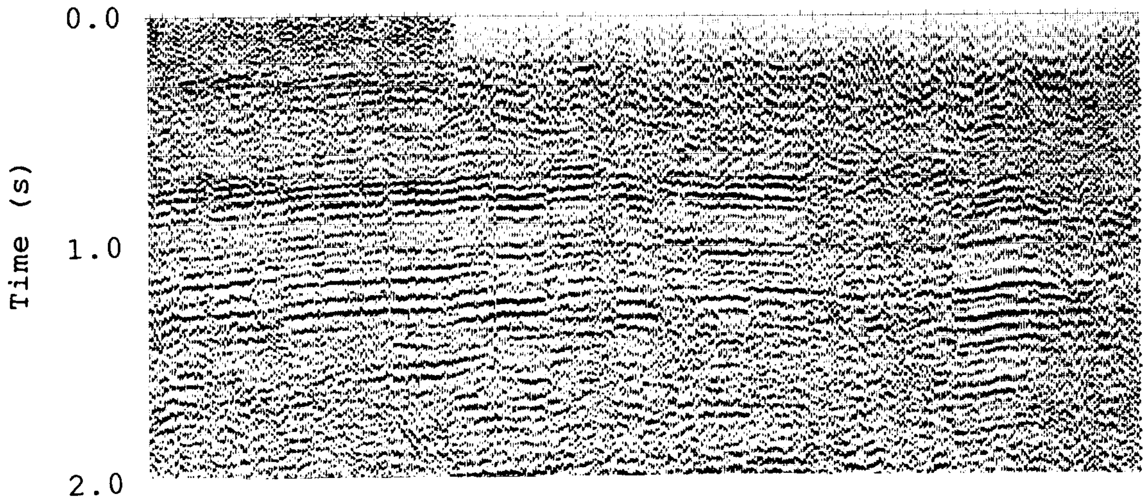

Fig. 7b. Common-receiver stack with simulated annealing statics.

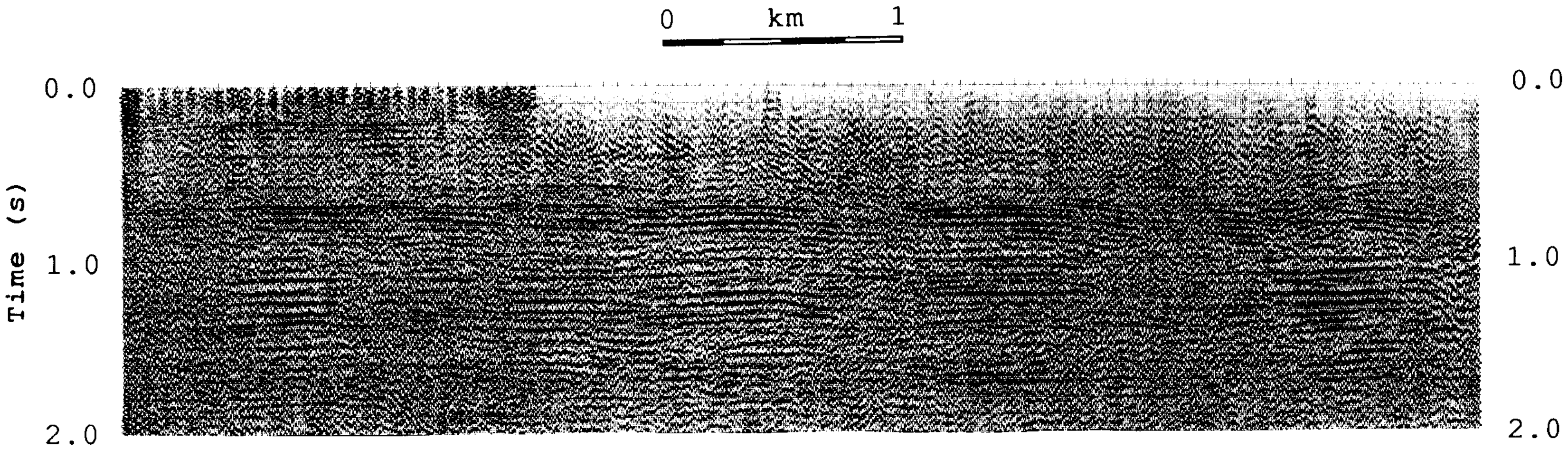

Fig. 8. Stack section with residual receiver statics computed in random order by stack-power optimization.

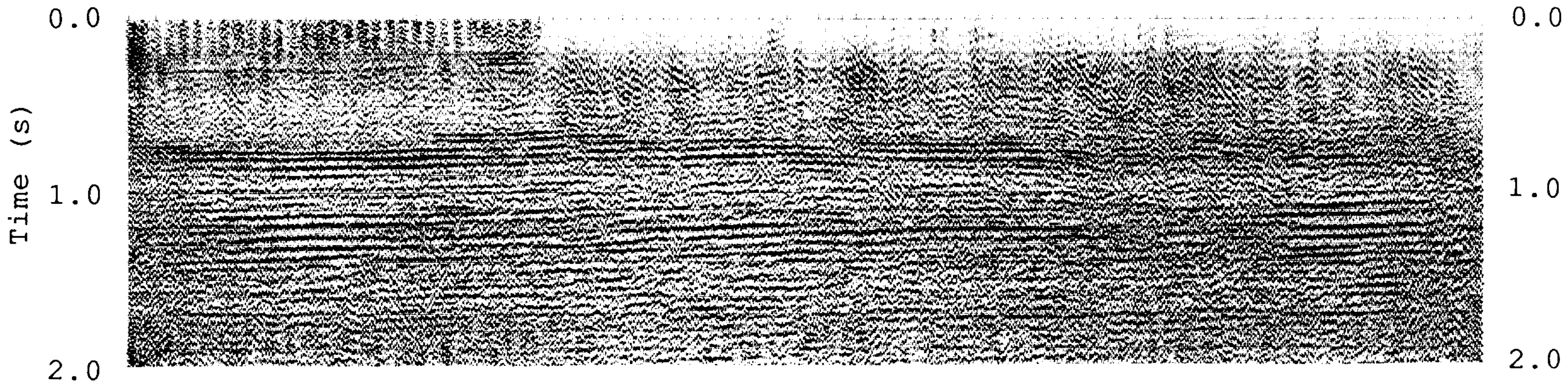

Fig. 9. Stack section with residual receiver statics computed by stack-power optimization with a 32 ms constraint on static jumps between adjacent receivers.

CONCLUSIONS

Our results indicate that residual-statics computations for *P-SV* data require the added flexibility of constraining the source and receiver statics independently, regardless of the algorithm used (i.e. Gauss-Seidel or stack-power optimization). This flexibility permits source statics computed previously using the vertical-component (*P-P*) data to be used as a hard constraint. We also agree with Vasudevan et al. (1991) that optimization of the stacking power without regard for trace-to-trace coherence can lead to undesireable results. We have developed a crosscorrelation technique that minimizes the power of the trace-mixed stack. Mixing with a small number of traces (e.g. 3) appears to be adequate to solve this problem.

We conclude that simulated annealing requires too much computer time to be used routinely. Notwithstanding the time spent determining the critical temperature and establishing a cooling schedule, the method is impractically slow, and a faster method is needed. We have tried several suggestions made by Dahl-Jensen (1989), such as solving for the source/receiver statics in random order, and constraining the statics to be smooth. Our tests appear to contradict Dahl-Jensen's findings.

Given the very difficult statics for this line compared to other *P-SV* datasets that we have processed, we believe that our trace-mixed stack-power optimization method will work reasonably well for most lines. On more challenging lines, some statics busts are unavoidable, as with most techniques. However, these are considerably easier to pick by hand than the original statics.

FUTURE WORK

We have begun to investigate automatic methods for removing the static bust problem, either during or after the inversion, using various types of smooting criteria and filtering operations (eg. running median). In addition, if only the receiver statics are required, then some method of optimizing the coherence of the common-receiver stack, rather the power of the CMP (or CCP) stack, is an obvious direction to pursue, since the busts are more obvious on the receiver stack. Optimization in the receiver-stack domain may also be faster, since it would involve the crosscorrelation between ordinary data traces, rather than supertraces. Consequently, simulated annealing may become more practical for this alternative statics-inversion scheme. Finally, forms other than the Gibbs distribution have been proposed for the prior probability function (Szu and Hartley, 1987). These lead to an algorithm than does not have a direct physical analog, but one that may be better suited to the statics inversion problem.

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