Fast Global Optimization Applied to Residual Statics.

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Outline

A. Introduction.

B. Major Accomplishments.
- Paper on TRUST in Science. May 1997.
- R&D 100 Award. June 1998.

C. Significant Results.

D. Plans for Future Work.

Introduction.

A. Problem.

- Surface-consistent residual statics.
- Stack power maximization.
- Since many local maxima, need a global optimization method.

B. Approach.

- TRUST (Terminal Repeller Unconstrained Subenergy Tunneling).
- SPT (Stochastic Pijavskij Tunneling).

C. Results.

1. Improved TRUST and Invented SPT.
2. Two stack power bounds and disaggregation of the problem.
3. Have found many solutions with high stack power.

April 1996 Project Review

John DuBose provided ORNL with both FORTRAN code to calculate stack energy and with four synthetic data sets (small or medium and clean or noisy).

The small data set contained 24 shots and 50 receivers, for a total of 74 parameters.
The medium data set contained 77 shots and 77 receivers, for a total of 154 parameters.

By April 1996, we had solved the two small data sets and were beginning to work on the medium data sets.

The original version of TRUST could not solve the problem for the medium data sets!

Technical Progress May 1996

Performed a careful review of the structure of the equations in the code from John DuBose.
Upper bound on power and Coherence Factor.
Decouple the Components of the Stack Energy.

Good Solution June 1996

The medium data set has 77 shots and 77 receivers. The number of CMP is 133 and the average fold is 11. The number of traces is 1462 and the number of frequencies is 49.

DuBose did not tell ORNL the values of the static corrections until after ORNL had given their best estimate of the corrections. Initially, ORNL was told that the maximum value of the stack energy was more than 1303.

We applied TRUST to the 133 decoupled problems. We were able to find solutions that gave values for each coherence factor that were near 1.0.
The total energy for the 133 decoupled problems was 1327.6 (the maximum value).

The v coordinates were mapped back to the x coordinates to determine an initial guess for the 154 parameter global optimization problem.

The initial value for the energy was 1250.8. After 12 iterations, TRUST found the maximum value at 1315.8.

New Data Set **Nov. 1996**

The large data set has 100 shots and 216 receivers.
The number of CMP is 423.
The number of traces is 4776 and the number of frequencies is 118.

Time per iteration is 100 times longer than for the medium data set.

Base Energy (x = 0) = 882.
Upper Bound. G = 6589.

We applied TRUST to the 423 decoupled problems.

Most of the best values for the coherence factor were much less than 1.0.

The total energy for the 423 decoupled problems is 2706. (Decoupled Upper Bound)

Preliminary Solution Dec. 1996

The 4776 v coordinates were mapped back to the x coordinates to determine an initial guess for the 316 parameter global optimization problem.

The initial value for the energy was 1035.
The initial valley was 2183.

After 98 iterations, TRUST found the maximum value at 2366.

New Method by Ed Oblow.
SPT (Stochastic Pijavskij Tunneling)

Two phases:

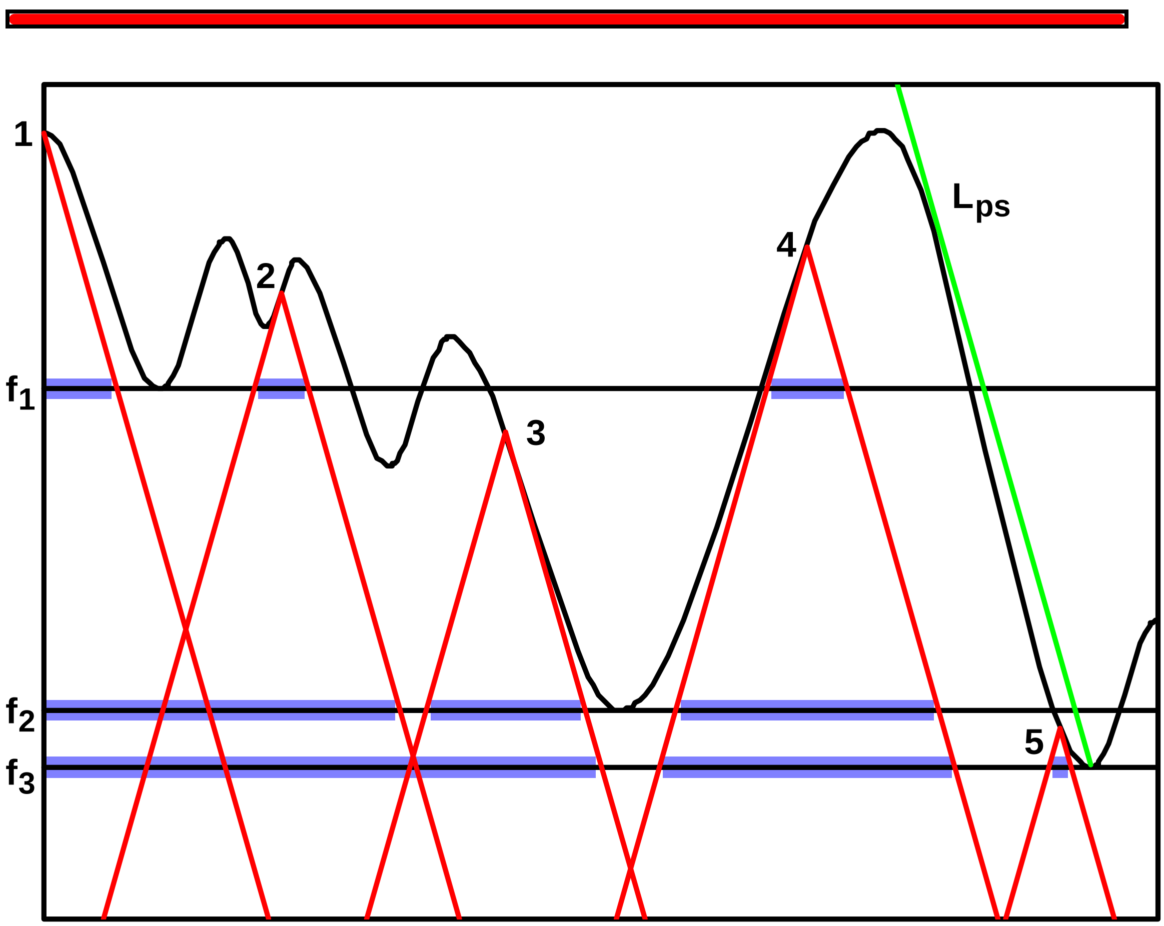
1. Descent to a local minimum.
2. Stochastic search.
   - Many line searches.
   - Rejection technique.
     - Use Pijavskij cones for rejection.
     - Importance sampling.

Key Concept: Lipschitz constant (L)

$$L = \max |df/dx|$$

L is the key parameter in the SPT algorithm.

Finding the global minimum for a 1D example using the SPT algorithm.



Discussion of Pijavskij figure.

1. Evaluate f(x) at point 1 (x_1).

2. Find local minimum (f_1). $f^* = f_1$.

3. P-Cone from x_1 rejects part of x-axis.

4. Evaluate at point 2 (x_2). $f(x_2) > f^*$.

5. P-Cone from x_2.

6. Evaluate at point 3 (x_3). $f(x_3) > f^*$.

7. P-Cone from x_3.

8. Evaluate at point 4 (x_4). $f(x_4) < f^*$.

9. Find local minimum (f_2). $f^* = f_1$.

10. P-Cones from $\{x_i\}$ reject most of x-axis.

11. Evaluate at point 5 (x_5). $f(x_5) < f^*$.

12. Find local minimum (f_3). $f^* = f_3$.

13. Evaluate at more points until all of the domain is rejected.

14. f_3 is the global minimum.

Current Solution Dec. 1997

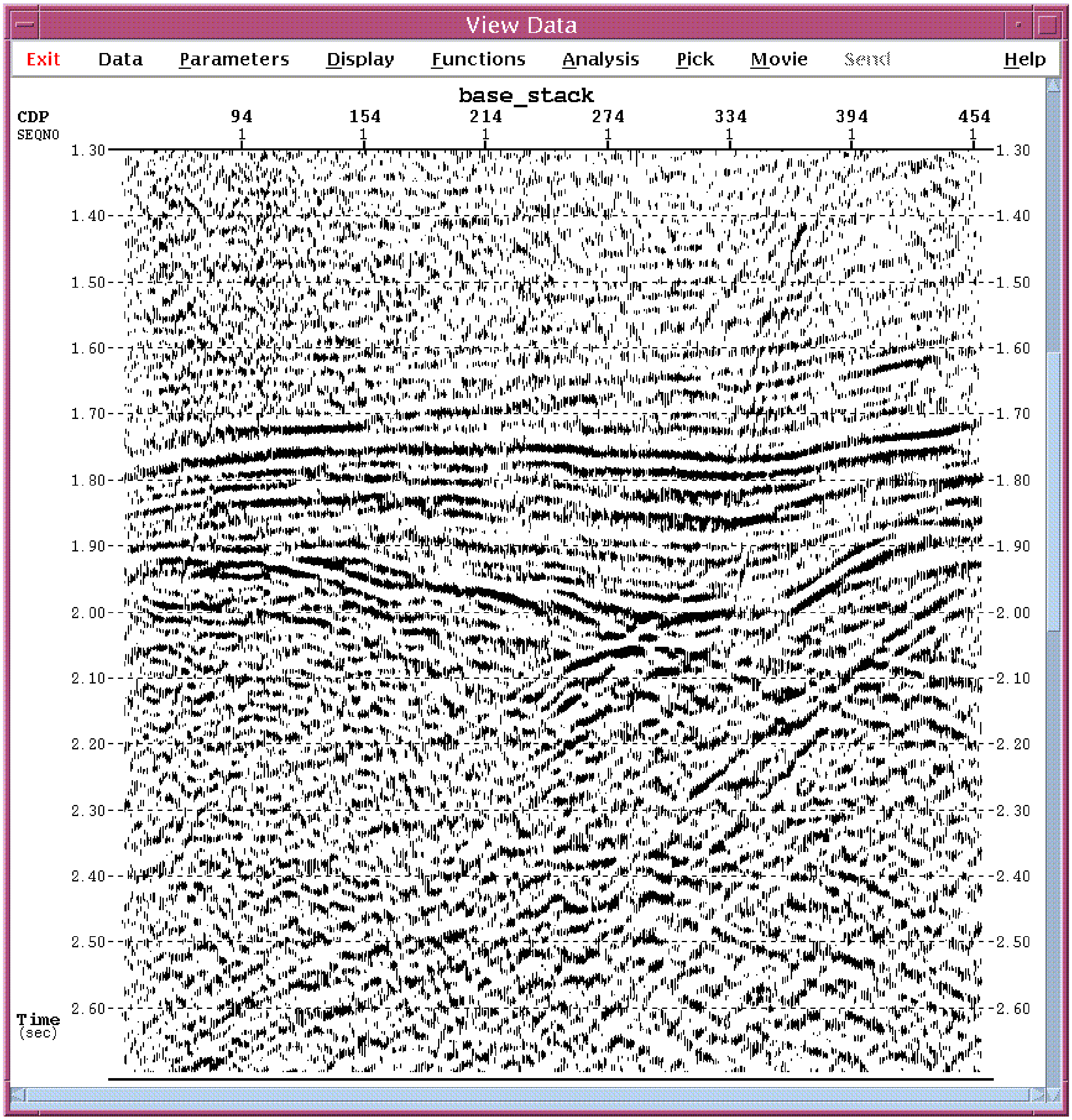
Upper Bound. G = 6589.
Decoupled Upper Bound = 2706.

Best Solution = 2441.

Have 22 points with energy above 2365.

Are the points distinct?
Yes. Significant distance after removal of the null space components.

How to compare?
Distance norm vs Energy norm.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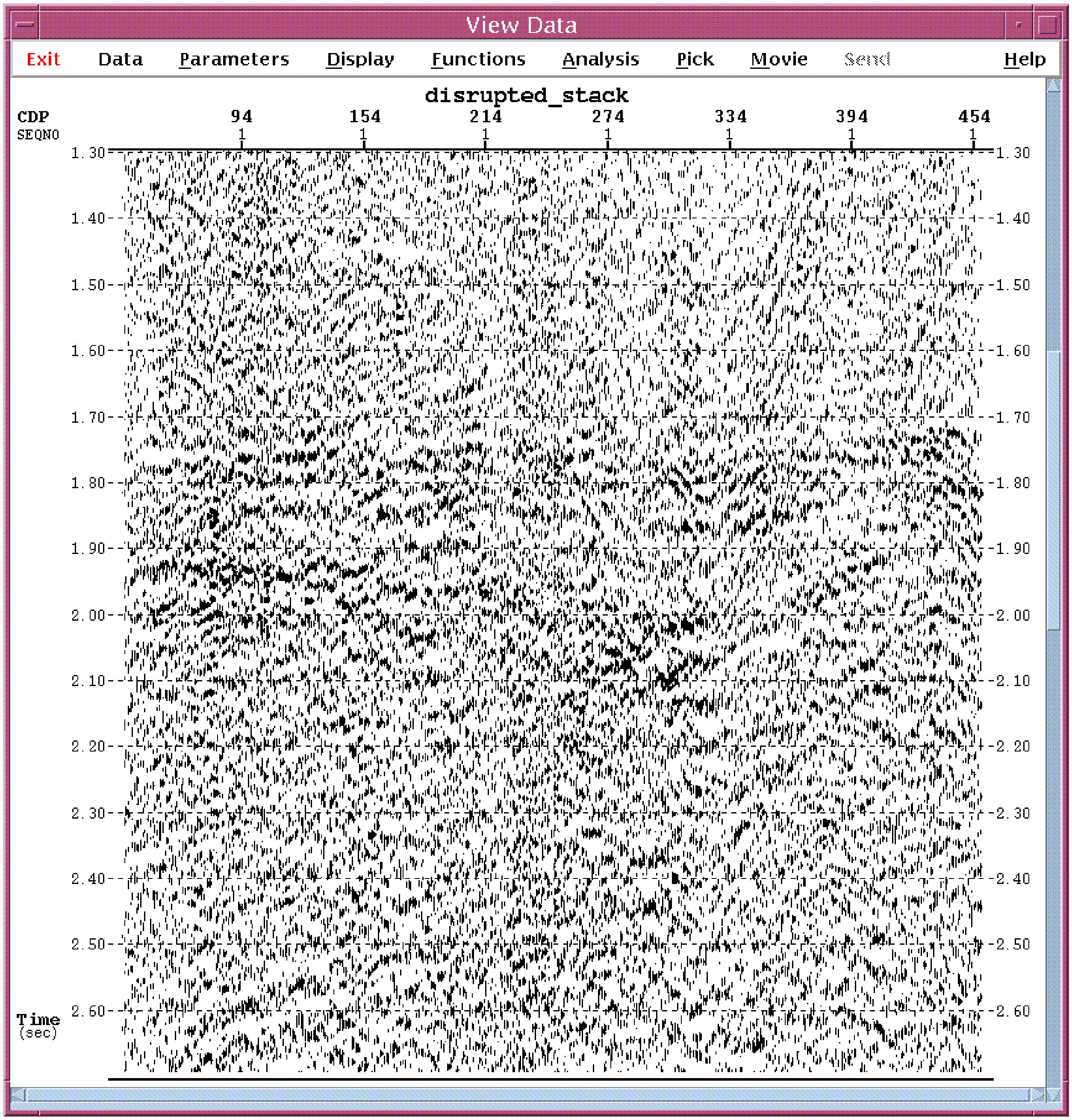
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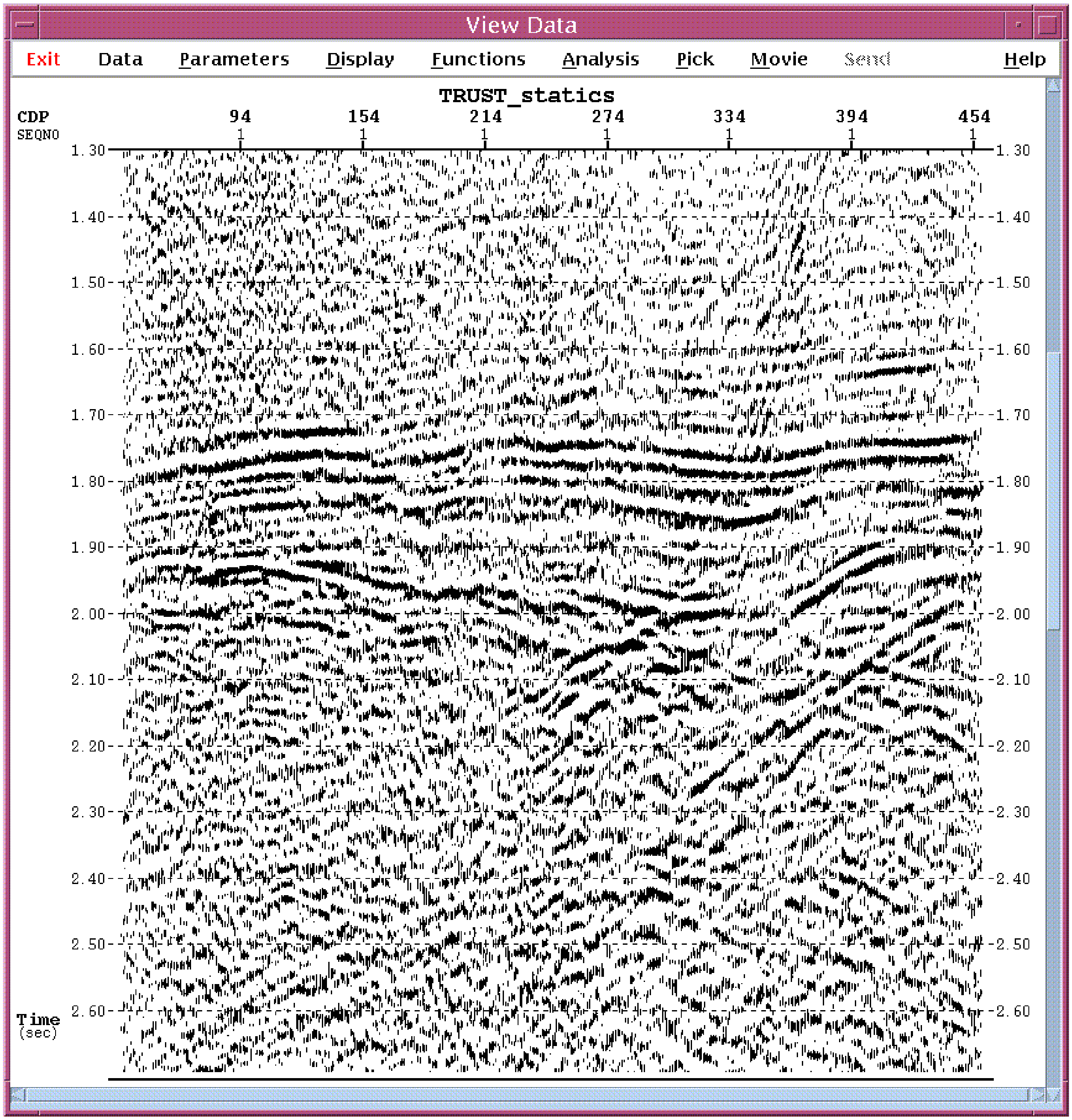
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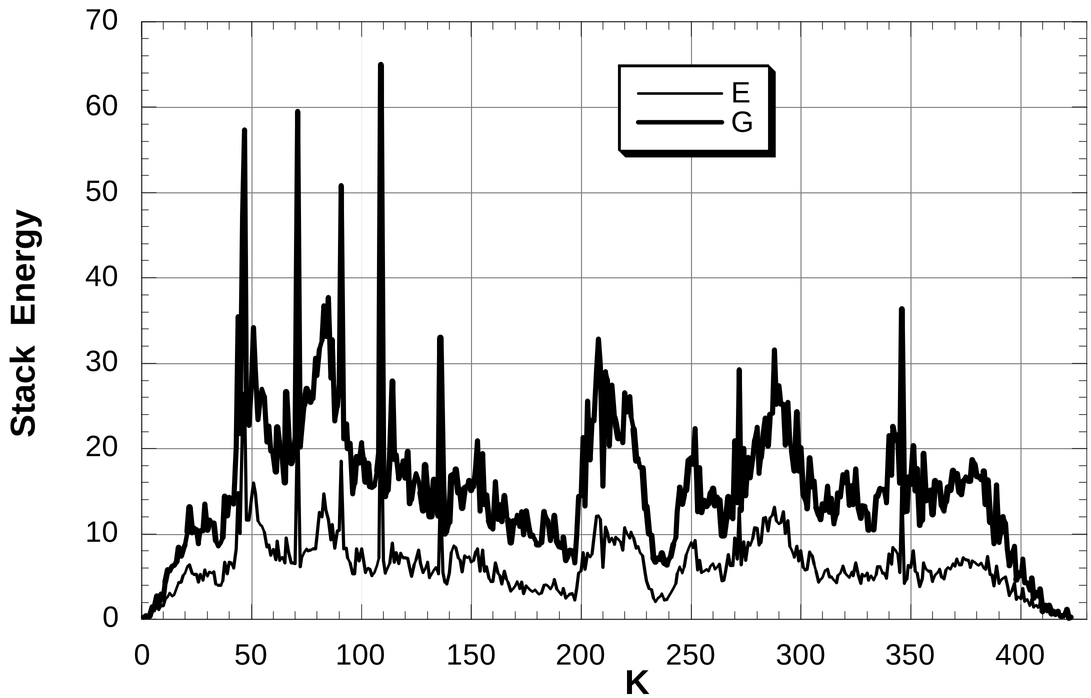
Time
(sec)

The stack power (E) and the upper bound (G) for each CMP.

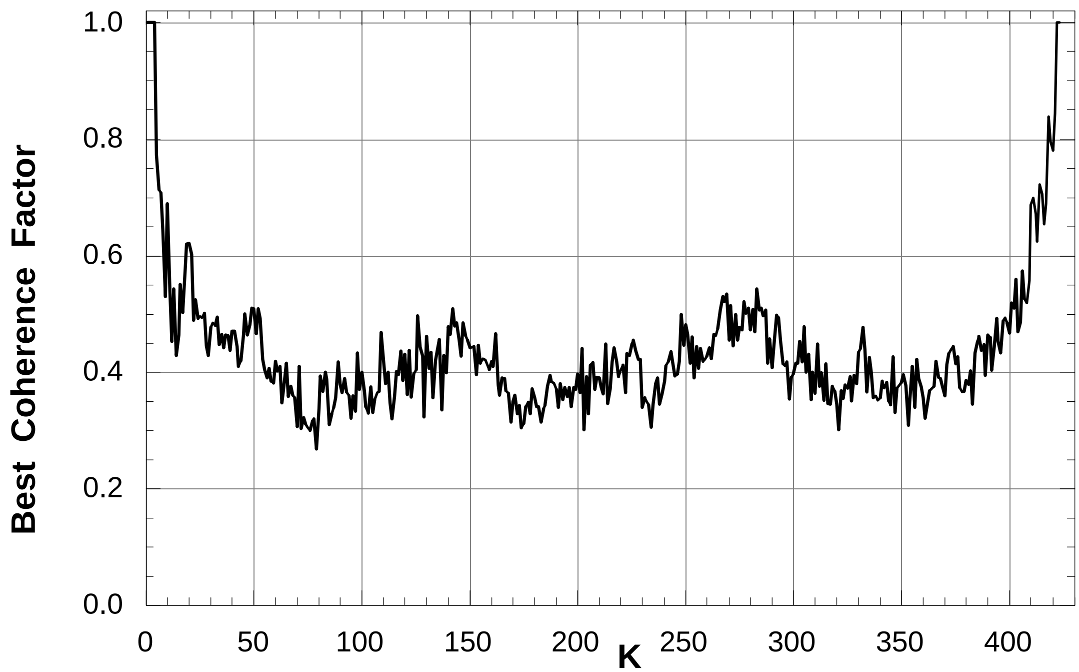
$E = \sum_k E_k = 2441.$ $\quad G = \sum_k G_k = 6589.$



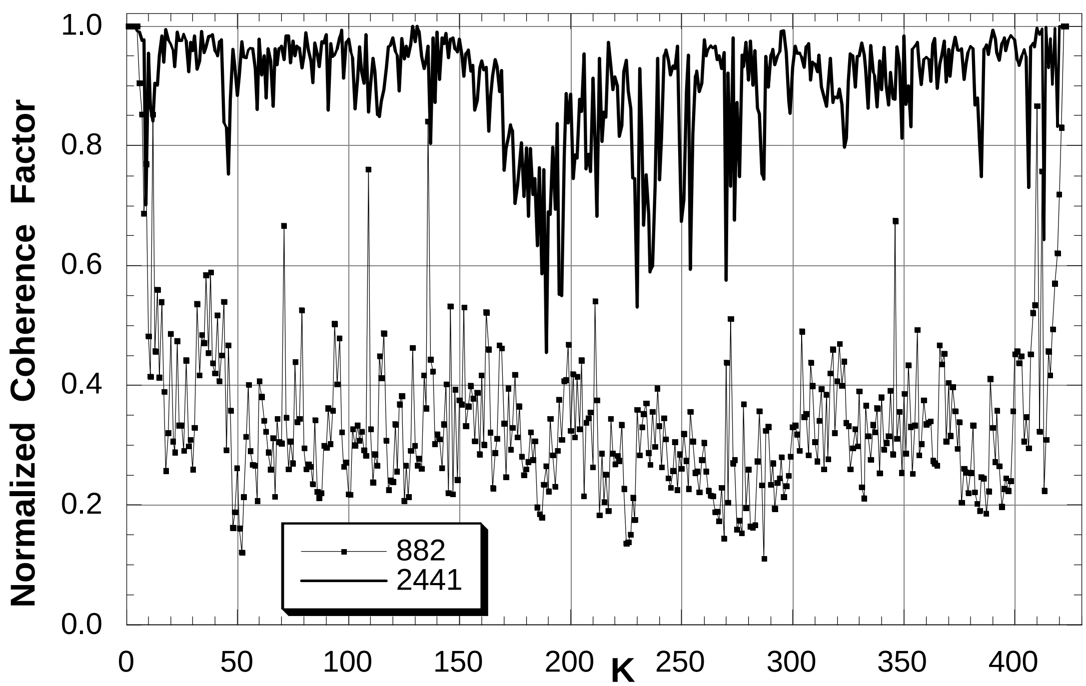
The best coherence factor.

The coherence factor (Q_k) is: $Q_k = E_k/G_k$

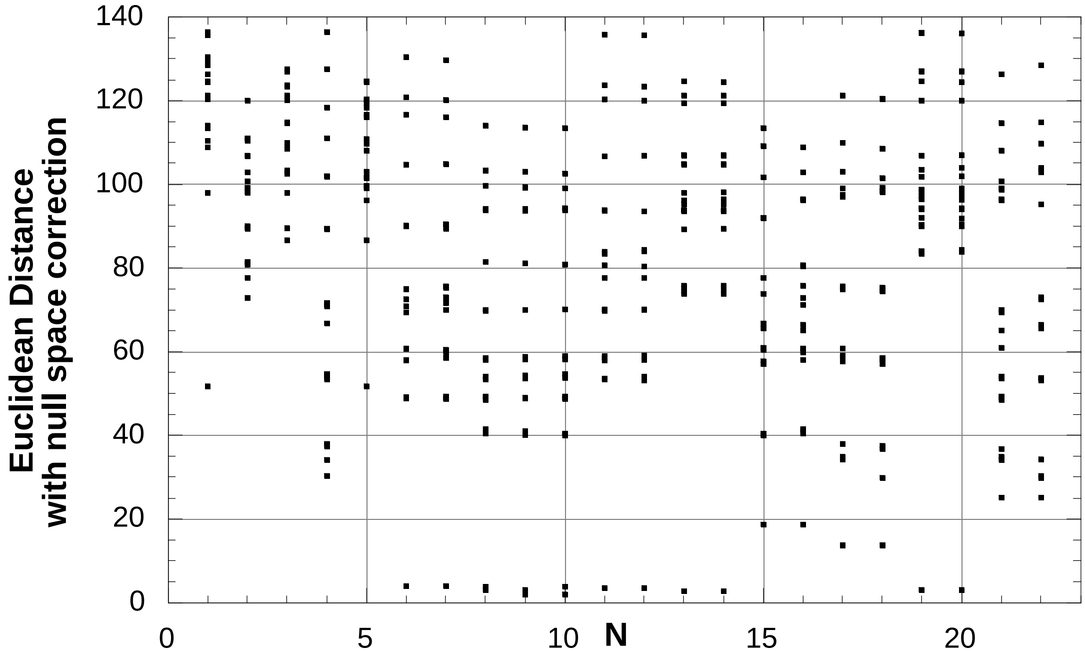
Best means use decoupled upper bound for E_k.



The normalized coherence factor for two cases: 882 and 2441.



The Euclidean distance between the 22 vectors after null space corrections.



Power Norm.

Two cases: c and d.

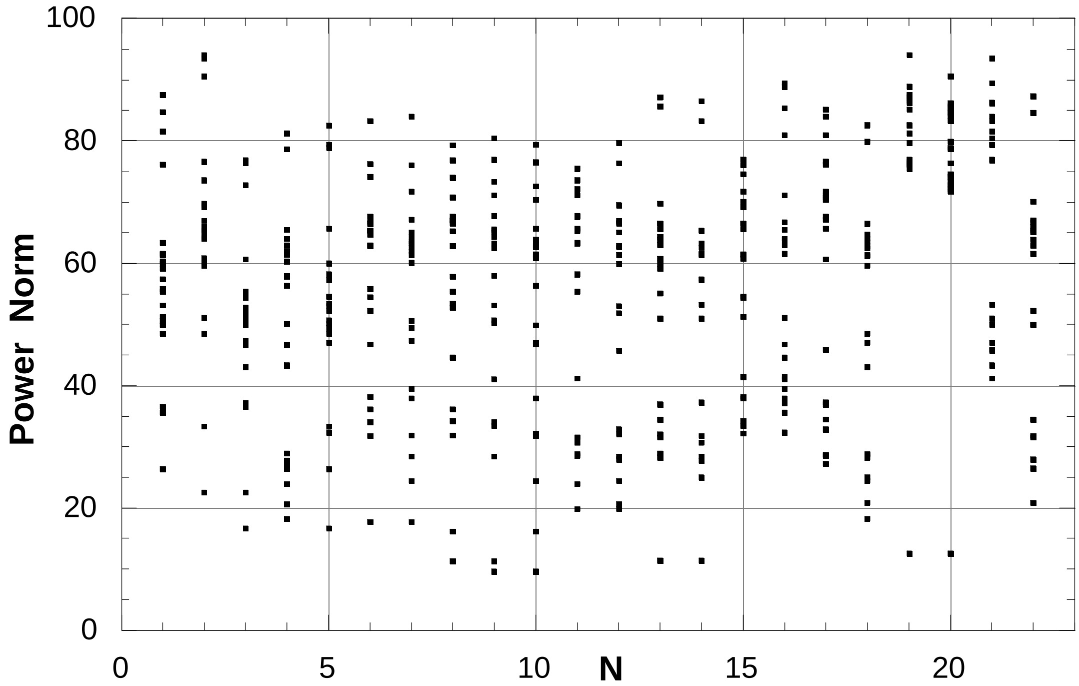
$$E^c = \sum_k {}^cE_k \qquad E^d = \sum_k {}^dE_k$$

$$\Delta_{cd} = \sum_k |\, {}^cE_k - {}^dE_k \,|$$

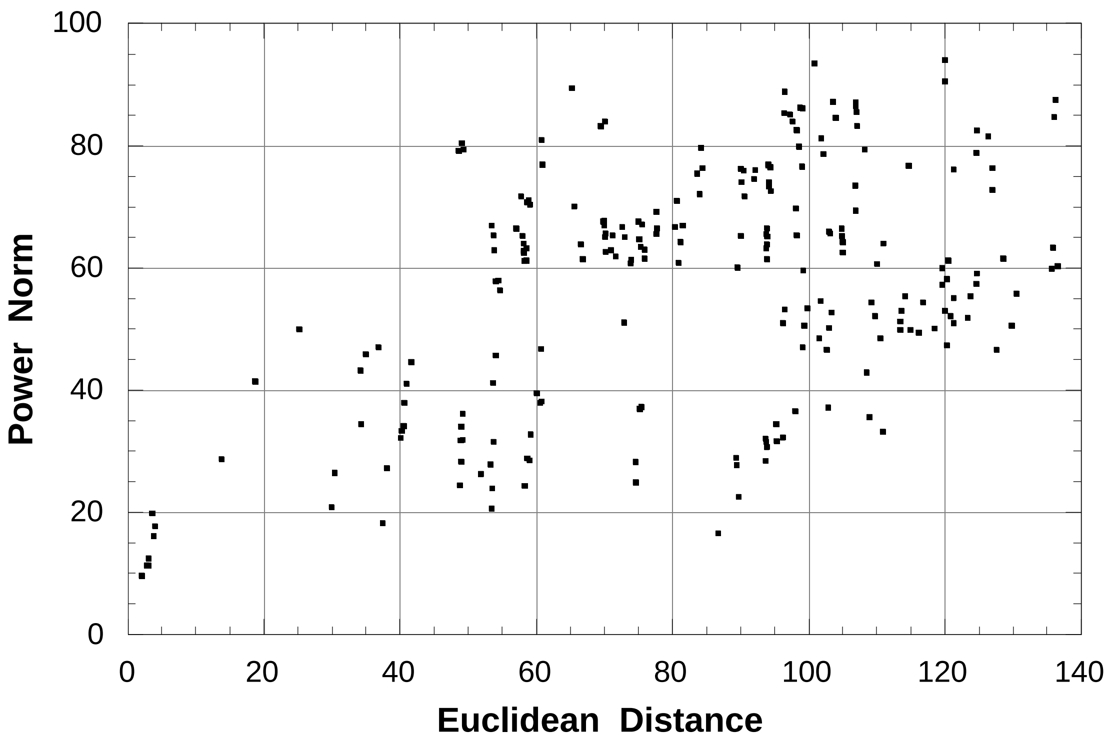
$$\varepsilon_{cd} = |\, E^c - E^d \,| \leq \Delta_{cd}$$

$$\beta = \Delta_{cd} - \varepsilon_{cd}$$

The power norm distance between the 22 vectors.



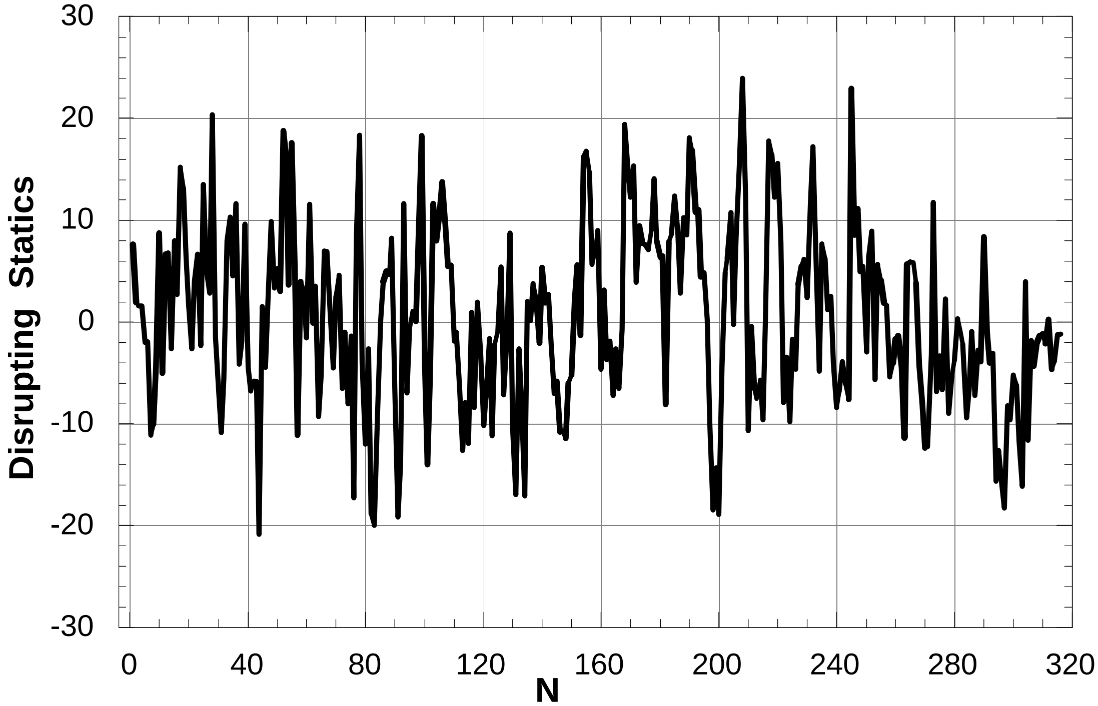
Correlation between the power norm and Euclidean distance.



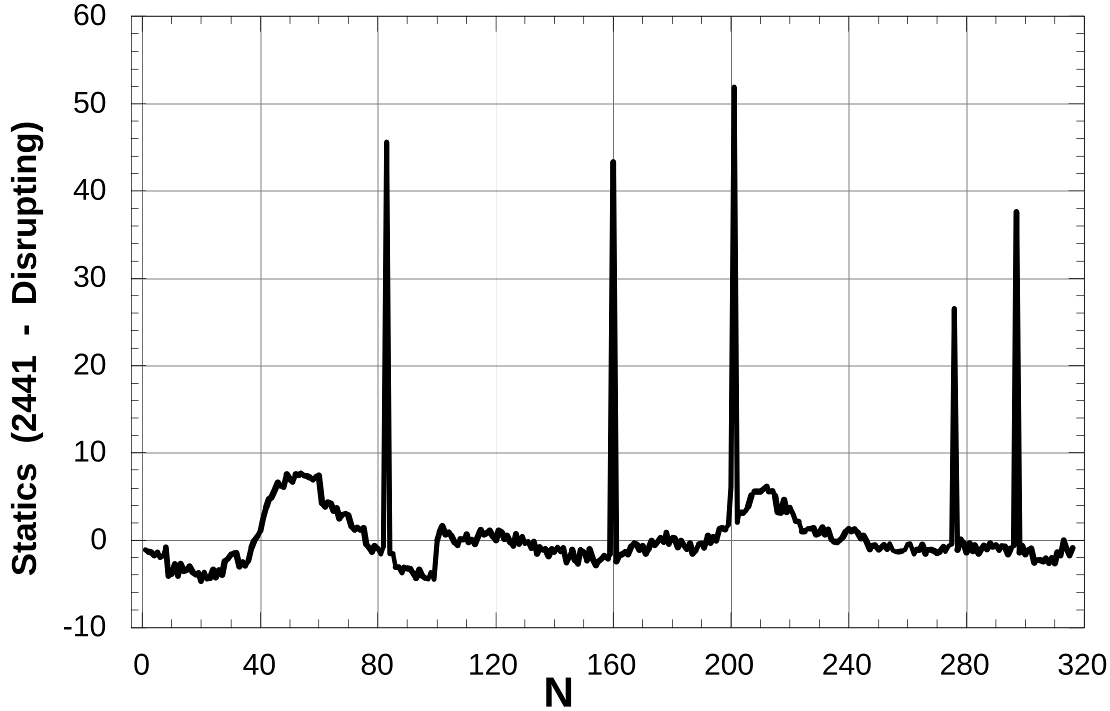
None zero but cluster in lower left corner.

Weak correlation (R^2 = 0.22)

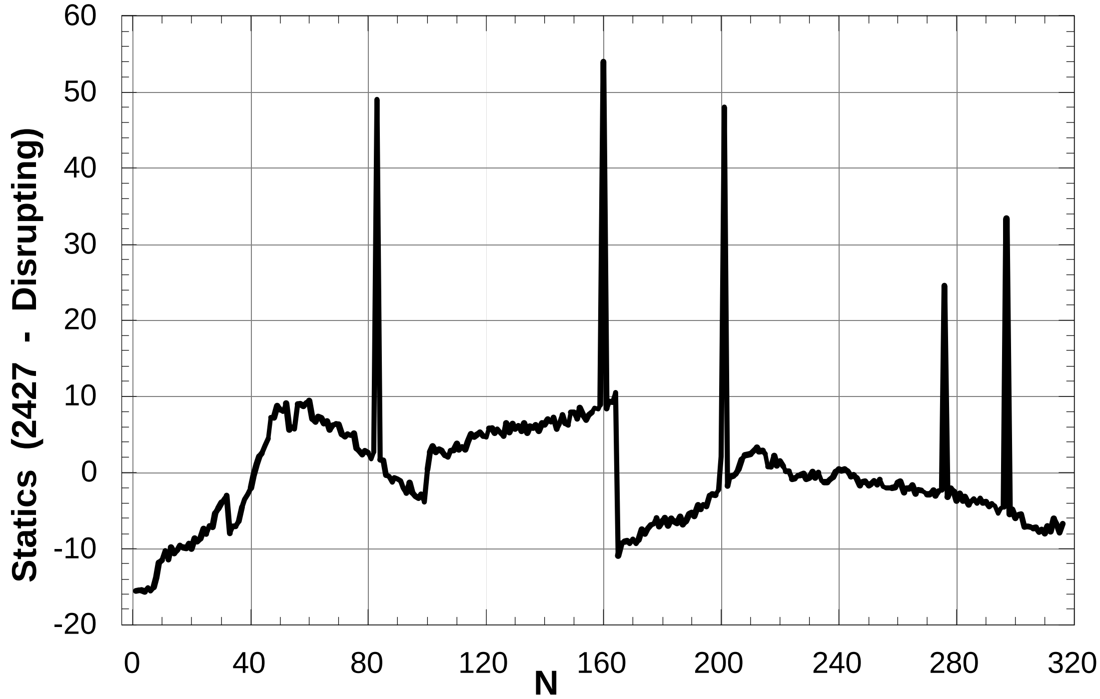
The disrupting statics that were applied to the original seismic data to produce the input data for this project.



The difference between the statics for the 2441 case and the disrupting statics.



The difference between the statics for the 2427 case and the disrupting statics.



Although we have cycle skips, the disrupting statics do not maximize the stack power!!

The power is 2349 for the disrupting statics. (Less than the 22 cases.)

Plans for Future Work.

Develop a methodology for predicting uncertainty in the forecasts of artificial neural networks (ANN).

Apply to ANN that are used to predict well log variables throughout an oil field using seismic data as inputs.

Initially, Chuck Glover and UNOCAL.

Recently, Jacob Barhen and DeepLook.

Nonlinear Uncertainty Analysis

The uncertainty analysis consistently combines field measurements with model predictions to simultaneously determine best estimates and covariance matrices for both model parameters and model predictions.

The problem is formulated in terms of a Bayesian loss function and solved as a constrained optimization problem that links the parameters to the predictions.

Sensitivity matrices are used to propagate the uncertainties.

The solution to the optimization problem ensures uncertainty minimization and best parameter estimates.

We expect our method to be significantly better than the current state-of-the-art methods.