Report on SCEC 2003 funding

*A contribution to the CMM: 3D surface displacements from the Landers and Hector Mine earthquakes derived from InSAR and GPS observations*

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This proposal was planning on providing the SCEC community with a "best" estimate of the co-seismic displacement fields using all available InSAR and GPS data from both earthquakes in terms of standardized east, north, and vertical components, Ux, Uy, Uz. Such coseismic displacement data sets will prove valuable to both modelers of the coseismic rupture (dynamic and static) as well as for construction of the CMM. By providing the data in an Ux, Uy, Uz format, we can easily take advantage of the redundancy of multiple interferograms and relieve the end user from worrying about the complexity of satellite viewing geometry such as satellite range dependent LOS angles. The project got side-tracked by our concern for adequate treatment of the noise structure in the InSAR data. This detour is nearly complete.

Previous combinations of InSAR data used a single acquisition of data from each of the possible viewing geometries, i.e., 1 ascending scene, 1 descending scene, and one azimuth offset scene. One would like to combine all the available acquisitions of InSAR data; however, one needs to deal with phase unwrapping holes in individual scenes due to phase decorrelation, to account for common acquisitions used in different interferograms, and to have the appropriate weights or variance estimates when combining data with different noise levels. In addition, the final product needs to come with some kind of covariance estimates. Over the last year, under this SCEC project, we have spent most of our time trying to deal with the error estimates, and how to incorporate those estimates into data sampling schemes (a computational requirement), and finally into slip models.

In a previous study, we estimated tropospheric delays from the SCIGN GPS network to form ensembles of pseudo-InSAR measurements, to look at the average covariance as a function of horizontal and vertical distance between two pixels [*Emardson et al*., 2002]. This approach is relevant when we have hundreds of scenes to combine. However, at the present, we are unfortunately restricted to a handful of scenes and we felt it was better to investigate the covariance structure of each interferogram directly. In figure 1, we show one such estimate of the covariance from a co-seismic interferogram in which a preliminary model of the co-seismic displacement field has been removed. Models of atmospheric turbulence suggest that spatial correlations caused by turbulence follow a power law distribution. The best fit power law is also shown in Figure 1 and does a reasonable job of fitting the covariance as a function of distance between two points. The positive and negative oscillations in the covariance at distances greater than 20 km correspond to atmospheric features such as lee waves.

Due to computational limitations associated with calculating Green's functions for each source/pixel pair, one really needs to use the data in the most efficient way possible. Previously, in our study of the Hector Mine EQ, we sampled the interferograms with spacing proportional to the curvature of the line of sight displacement field, with the assigned value for a given sample being the mean of the displacements for the area it

represented. This approach worked reasonably well, but ignored data covariances. We can now take these covariances into account during the sampling process.

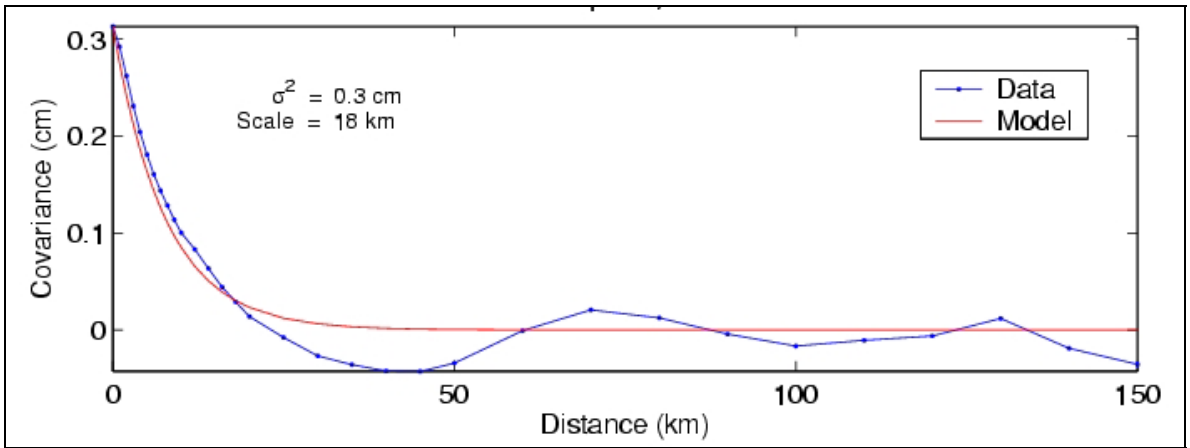


*Figure 1: Average isotropic covariance structure of noise in a single interferogram. Blue dotted line indicates the computed covariance vs. distance. Red line indicates the power law distribution that best fits the observed values.*

Our goal is to choose a distribution of points that are spatial averages over the input interferogram, so that we have more data points in regions where there the displacement field has more structure due to the earthquake and few data points in regions that are far from the fault. The ideal distribution of averaged points would maximize the number of data retained while diagonalizing the data resolution matrix. Towards this goal, we have developed the following simple algorithm:

1. Begin with a coarse grid of points, each a spatial average over part of the interferogram (including all the covariances).
2. Calculate the data resolution matrix for this data point geometry.
3. For every point that is too highly resolved (above a given preset threshold), break it into four smaller regions.
4. Continue until each point is below but close to the resolution threshold.

Essentially, we increase the number of data points until each point correlates with 2-5 surrounding points. This sampled data set is a great improvement over using the full interferogram, where data points far from the fault may correlate with thousands of other points. In Figure 2, we show the results of using this approach. The four sub panels correspond to a different iteration in our algorithm, starting from a coarse distribution of points. The first set of four panels shows the evolution in the number of points retained, and the local points used to calculate the local mean. In the second set of four panels, color indicates the line-of-sight (LOS) deformation from the interferogram, appropriately averaged over the area of the given box.

With our estimates of the full data covariance and the improved data sampling technique, we can now begin to stack multiple interferograms for a single data set of E, N, and U displacements for use by others. The proposed algorithm goes as follows:

1. Calculate a preliminary model for each data set using the “correctly” sampled data.
2. Stack the residuals from any given viewing geometry while keeping track of the covariances.
3. Using the stacked residuals from multiple viewing geometries (LOS and/or pixel tracking), calculate the best E, N, and U components.
4. Iterate between steps 2 and 3 to fill holes in the original stacked residuals using a POCS approach.
5. Add the model back in.

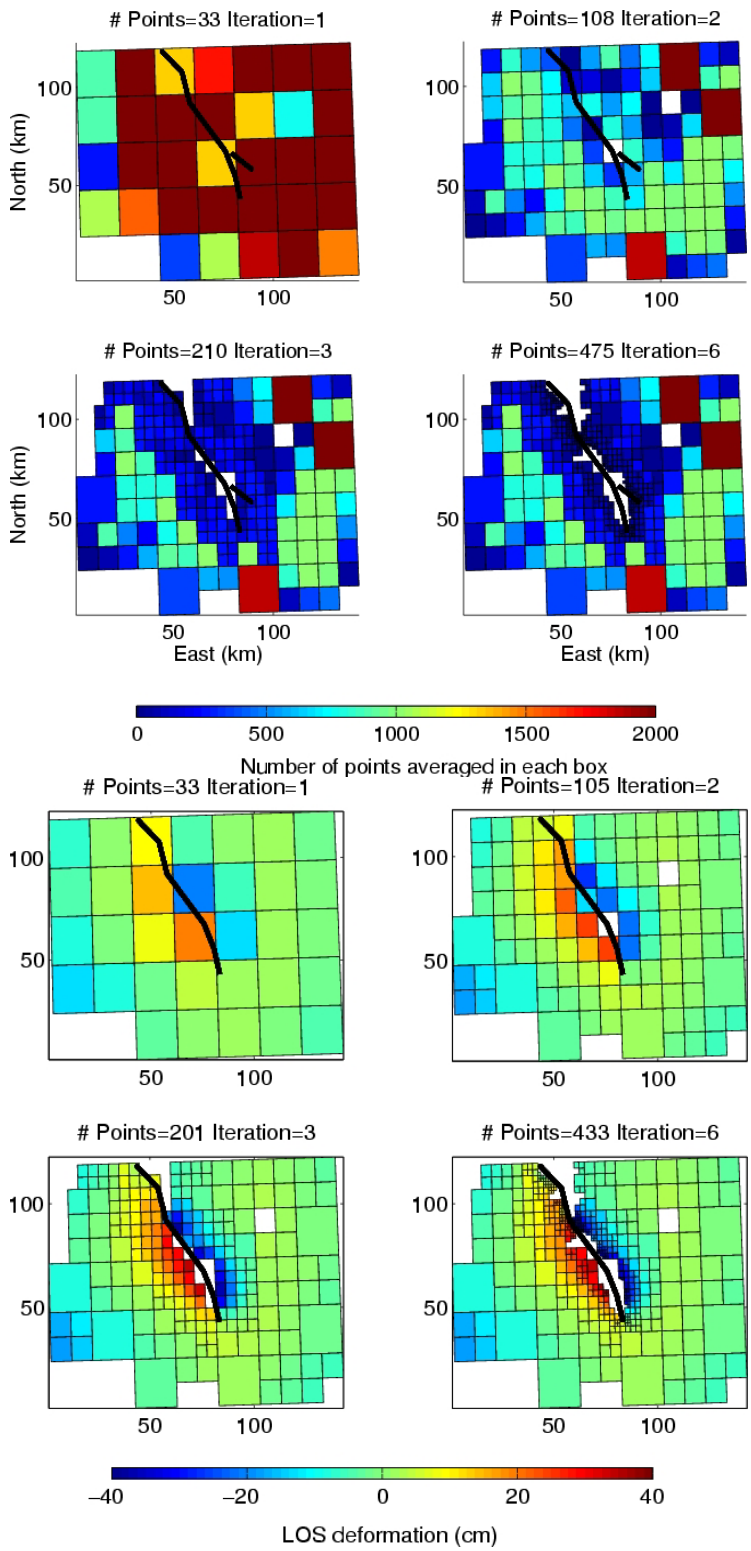


*Figure 2: (Top set) Example of the iterative data sampling scheme including use of the full data covariance with an objective of maximizing the number of retained samples while diagonalizing the data resolution matrix. Color represents the number of points used in the average for a given box. Generally larger boxes have more points. However, some regions are too noisy to be phase unwrapped and they are not considered in the data sampling. Thus there is some variability in the number of points per box of a given size. Heavy black lines indicate the fault planes for this particular earthquake. This example is for a large strike-slip earthquake in Iran. (Bottom set) Same as above, but with color indicating the estimated satellite line of sight displacement for each square region.*