

# FRINGE 2011 WORKSHOP

# Deformation rate estimation on changing landscapes using Temporarily Coherent Point InSAR

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Stable vs. Changing Landscapes

On stable landscapes there are abundant scatterers that can keep visible during a long observation time span

In well-developed urban areas, dense persistent scatterers can be identified

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Stable vs. Changing Landscapes

However on changing landscapes there are abundant scatterers that cannot keep visible during a long observation time span

> In developing urban areas, persistent scatterers cannot be densely identified

 $\mathbf{O}$ 



2007

Most developing countries are undergoing surprisingly fast urbanization...

Townscapes have changed significantly, raising difficulties for current MT-InSAR techniques to get detailed defo. maps...





Urban renewal and



Persistently Coherent Point vs. Partially Coherent Point

Persistently Coherent Point-Visible over the whole observation time span



Partially Coherent Point – Visible over a part of observation time span



2000

2001

2002

2004



2010 (year)



Can we identify both persistently coherent points and partially coherent points simultaneously and retrieve deformation reliably from these points?

- **Temporarily Coherent Point**
- not necessary to keep coherent during the whole time span
- including persistently coherent point and partially coherent point



(Courtesy of A. Hooper)

### **TCP identification:** Image-pair based methods

### Offset deviation<sup>[1]</sup>

During the coregistration procedure, standard errors of the estimated offsets from strong scatterers is less sensitive to the window size and oversampling factor used in the image cross-correlation compared with those from distributed scatterers<sup>[2]</sup>.

$$\mathbf{OT_j} = \begin{bmatrix} ot_{j1} & ot_{j2} & \cdots & ot_{jN} \end{bmatrix}$$
  
std( $\mathbf{OT_j}$ ) < 0.1

### Coherence map

Suitable for image pairs with short baselines (spatial, temporal and Doppler) Coherence is used as threshold to select partially coherent points in [3][4]

 Zhang, L., Ding, X.L., & Lu, Z. (2011a). *ISPRS Journal of Photogrammetry and Remote Sensing, 66*, 146-152
 Bamler, R., & Eineder, M. (2005). *IEEE Geoscience and Remote Sensing Letters, 2*, 151-155
 Biggs, J., Wright, T., Lu, Z., & Parsons B. (2007). Geophysical Journal International, 170, 1165-1179.
 Biggs, J., Burgmann, R., Freymueller, J.T., Lu, Z., Parsons, B., Ryder, I., Schmalzle, G., & Wright, T. (2009). Geophysical Journal International, 176, 353-367

TCP: keep coherent in more than \*\*% image pairs (say, 70%) We exactly know in which interferogram the selected TCPs are coherent.

**TCP identification: Image based method** 

👁 Amplitude Mad-Median Ratio (AMMR)

 $\sigma_{v} \cong \frac{\sigma_{A}}{m_{A}} \implies \sigma_{v} \cong \frac{Mad_{A}}{Median}$ 

Median absolute deviation Mad(X)=median(abs(X-median(X))

A point with scaled intensity time series (25): PS? No; TCP? Yes!

[0.1, 0.2, 0.2, 0.3, 0.2, 0.2, 0.3, 0.8, 0.85, 0.9, 0.9, 0.92, 0.92, 0.91, 0.94, 0.93, 0.95, 0.95, 0.92, 0.94, 0.92, 0.91, 0.91, 0.92, 0.93];

$$\sigma_{v} \cong \frac{\sigma_{A}}{m_{A}} = 0.45 \quad \sigma_{v} \cong \frac{Mad_{A}}{Median_{A}} = 0.03$$

We do not know in which interferogram the selected TCPs are coherent.

**TCP Parameter Estimator** 

To resolve DEM error and linear deformation rate without the need of phase unwrapping

Observations are differential phases at the arcs (point pairs) in multi-master interferograms with short baselines

Core algorithms:

L-2 norm (least squares) estimator with ambiguity detector[5] L-1 norm estimator

[5] Zhang, L., Ding, X.L., & Lu, Z. (2011b). *IEEE Transactions on Geoscience and Remote Sensing, 49,* 547-556

### The system of observations

Δ

N

$$\phi_{l,m}^{i} = \phi_{lopo,l,m}^{i} + \phi_{defo,l,m}^{i} + \phi_{atmo,l,m}^{i} + \phi_{orbit,l,m}^{i} + \phi_{noise,l,m}^{i}$$
For each arc, we have
$$\phi_{defo,l,m}^{i} = -\frac{4\pi}{\lambda} \Delta r_{l,m}^{i} = -\frac{4\pi}{\lambda} \sum_{j=S_{i+1}}^{M_{i}} (t_{j} - t_{j-1})v_{j}$$

$$= \beta_{i}V$$

$$\psi_{atmo,l,m}^{i} = -\frac{4\pi}{\lambda} \frac{B_{\perp,l,m}^{i}}{r_{l,m}^{i} \sin \theta_{l,m}^{i}} \Delta h_{l,m}$$

$$= \alpha_{l,m}^{i} \Delta h_{l,m}$$

$$= \alpha_{l,m}^{i} \Delta h_{l,m}$$

$$= \alpha_{l,m}^{i} \Delta h_{l,m}, + \beta_{i} \Delta V + w_{l,m,l',m'}^{i} + \Delta \phi_{noise,l,m}^{i}, W = [w_{l,m,l',m'}^{i} - w_{l,m,l',m'}^{i} - w_{l,m,l',m'}^{i}]$$

$$How to resolve the parameters?$$

L-2 norm (least squares) estimator with ambiguity detector

This algorithm is suitable for TCPs identified by image-pair based methods

- Since we exactly know in which interferograms the selected TCPs keep high coherence, we can get a coherence index for each TCP
  - For each arc, only interferograms in which both points keep coherent are selected.

$$\begin{bmatrix} \Delta \hat{h}_{l,m,l',m'} \\ \Delta \hat{V} \end{bmatrix} = (A^T P^{dd} A)^{-1} A^T P^{dd} \Delta \Phi$$
$$\Delta \hat{\Phi} = A (A^T P^{dd} A)^{-1} A^T P^{dd} \Delta \Phi$$
$$r = \Delta \Phi - A (A^T P^{dd} A)^{-1} A^T P^{dd} \Delta \Phi$$

 $\Phi$  might have phase ambiguities!!



L-2 norm (least squares) estimator with ambiguity detector

Ambiguity detector  $Q_{\Delta\hat{\Phi}\Delta\hat{\Phi}} = A(A^T P^{dd} A)^{-1} A^T$   $Max(|r_i|) > c\sqrt{Max((Q^{dd})_{ii})} + 2\sqrt{Max((Q_{\Delta\hat{\Phi}\Delta\hat{\Phi}})_{ii}))}$ 

#### 🚯 TCP parameters

After removing modulo-2pi arcs, perform Arc-Point integration





### L-1 norm estimator

For TCPs selected by image based approach, we do not exactly know in which interferograms the TCPs are coherent

When taking all interferograms as observations, we need to design a robust estimator to suppress the effect of "outliers" (i.e., decorrelated phases and phase ambiguities at arcs)

L-1 norm estimator is a good choice since it is less sensitive to outliers than LS

With L-1 norm estimator, we do not need to remove arcs having decorrelated phases and phase ambiguities!!

### L-1 norm estimator

We how to perform L-1 norm estimation? L-1 norm estimator is to find  $\hat{x}$  as follows:  $\hat{x} = \arg \min_{x} \|b - Ax\|_{1}$  $\Delta \Phi = A \begin{bmatrix} \Delta h_{i,m,i',m'} \\ \Delta V \end{bmatrix} + W \longrightarrow \mininze \sum_{i} \left| \Delta \phi_{i,m,i',m'}^{i} - \sum_{j} A_{ij} \begin{bmatrix} \Delta h_{i,m,i',m'} \\ \Delta V \end{bmatrix} \right|$ 

Solution by iteratively reweighted least squares used in [6] for robust SBAS

#### Solution by linear programming

[6] Lauknes, T. R., Zebker, H.A. and Larsen Y. (2011). IEEE Transactions on Geoscience and Remote Sensing, 49, 536-546

L-1 norm estimator: Solution by linear programming

minimize 
$$\sum_{i} \left| \Delta \phi_{l,m,l',m'}^{i} - \sum_{j} A_{ij} \begin{bmatrix} \Delta h_{l,m,l',m'} \\ \Delta V \end{bmatrix} \right|$$

minimize  $\sum_{i} f_{i}$ subject to  $f_{i} - \left| \Delta \phi_{l,m,l',m'}^{i} - \sum_{j} A_{ij} \begin{bmatrix} \Delta h_{l,m,l',m'} \\ \Delta V \end{bmatrix} \right| = 0$ 

minimize  $\sum_{i} f_i$ 

subject to 
$$-f_i \leq \Delta \phi_{l,m,l',m'}^i - \sum_j A_{ij} \begin{bmatrix} \Delta h_{l,m,l',m'} \\ \Delta V \end{bmatrix} \leq f_i$$

With any linear programming software package, it can be solved easily.

### The performance of the L-1 norm estimator?



Even though the arc contains decorrelated phases as well as phase ambiguities, the L-1 norm estimator can precisely resolve the defo. rate!

### Case study



Data: 38 Envisat/ASAR images acquired from 2003 to 2010 81 interf. selected with baseline thresholds: 250day,150m and 300Hz



(Macau)

(Many buildings have been put up...)

### Case study

Image pair based methods:

TCP selection ~

Image based methods:

ADI: Amplitude Dispersion Index AMMR: Amplitude Mad Median Ratio



### Case study

#### LS estimator on TCPs selected by L-1 nor offset deviation selected

L-1 norm estimator on TCPs selected by AMMR



Consistent with ground measurements provided by DSCC of Macau

Results

# Case study: TCPInSAR with high resolution data

# Data

23 TSX SAR data from April 29, 2009 to November 11, 2010

Baseline threshold: 15m, 250d

15m: No external DEM is needed!



# Case study: TCPInSAR with high resolution data



Subsidence rate (mm/yr) -52 to -51 -51 to -49 -49 to -47 -47 to -45 -45 to -44 -44 to -42 -42 to -40 -40 to -38 -38 to -37 -37 to -35 -35 to -33 -33 to -31 -31 to -29 -29 to -28 -28 to -26 -26 to -24 -24 to -22 -22 to -21 -21 to -19 -19 to -17 -17 to -15 -15 to -14 -14 to -12 -12 to -10 -10 to -8.3 -8.3 to -6.5 -6.5 to -4.8 -4.8 to -3 -3 to -1.3 -1.3 to 0

The LOS deformation rate is up to 52 mm/yr The result has been validated by

benchmarks and CRs

The work is done in collaboration with Guoxiang Liu of SWJT Univ. China

The field work was performed by SWJT Univ.

### Conclusion

TCPInSAR is a promising tool for deformation monitoring on changing landscapes with multi-temporal SAR data.

TCPInSAR can identify both persistently and partially coherent points

Offset deviation or Amplitude Mad Median Ratio (AMMR)

TCPInSAR can estimate linear deformation rate (for partially coherent points) and deformation time series (for persistently coherent points) with no need of phase unwrapping

L-2 norm estimator with ambiguity detector L-1 norm estimator Thanks! Questions?

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