1. Quick recap

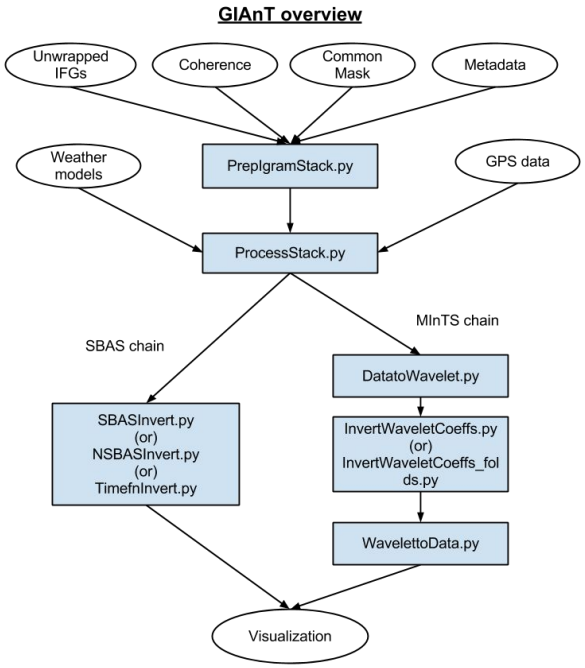
So far, we have gathered all the required network, unwrapped phase and coherence information into a HDF5 file using “PrepIgramStack.py” in the previous tutorial.

```
> cd /home/ubuntu/data/giant/napa/GIAnT
> h5ls Stack/RAW-STACK.h5
Jmat                     Dataset {30, 12}
bperp                    Dataset {30}
cmask                    Dataset {4165, 1650}
dates                    Dataset {12}
igram                    Dataset {30, 4165, 1650}
tims                     Dataset {12}
usat                     Dataset {12}
```

In this tutorial, we will apply optional corrections to the ingested stack and estimate the deformation time-series using the SBAS technique. We will also teach users to interactively visualize some of the time-series results.

2. Setting up the processing parameters

In the previous tutorial, we described how the dataset parameters are controlled using “data.xml”. In this tutorial, we will learn to set up the processing parameters using a similar XML file - “sbas.xml”. This processing file is specific for the SBAS set of time-series inversions (See figure below).



In the example dataset directory, you will find a script named “prepsbasxml.py” .

```
> cd /home/ubuntu/data/giant/napa/GIAnT
> less prepsbasxml.py
#!/usr/bin/env python

import tsinsar as ts
import argparse
import numpy as np

if __name__ == '__main__':
    g = ts.TSXML('params')
    g. prepare_sbas_xml(nvalid = 20, netramp=True, atmos='',
                        demerr = False, filt=0.25)

    g.writexml('sbas.xml')
```

The complete list of all configurable parameters in “sbas.xml” can be found in the GIAnT user manual. We describe the parameters that we have set up using prepsbasxml.py below:

nvalid	Used for NSBAS inversion. Determines the minimum number of interferograms that a pixel should be coherent to be considered for inversion.
netramp	Boolean parameter controlling the deramping of interferograms. In this case, the applied ramp corrections are consistent over the entire network.
atmos	ProcessStack.py can download weather model data and use that for stratified trophospheric phase delay correction. This is beyond the scope of this tutorial. We use a empty string to indicate that no weather model corrections are to be applied.
demerr	Boolean parameter indicating if a DEM error term needs to be estimated. The baseline information from ifg.list is used for DEM error estimation.
filt	Width of the Gaussian filter to applied to the raw time-series to obtain the smoothed estimates. The value of this parameter is in years.

See GIAnT user manual for complete list of options and default values.

```
> cd /home/ubuntu/data/giant/napa/GIAnT
> python prepsbasxml.py
```

To view the generated “sbas.xml” file,

```
> less sbas.xml
<params>
  <proc>
    <nvalid>
      <value>20</value>
      <type>INT</type>
      <help>Minimum number of coherent IFGs for a single pixel. If
zero, pixel should be coherent in all IFGs.</help>
    </nvalid>
    <uwcheck>
      <value>False</value>
```

```
      <type>BOOL</type>
    </uwcheck>
    <netramp>
      <value>True</value>
      <type>BOOL</type>
      <help>Network deramp. Remove ramps from IFGs in a network
sense.</help>
    </netramp>
    <gpsramp>
      <value>False</value>
      <type>BOOL</type>
      <help>GPS deramping. Use GPS network information to correct
ramps.</help>
    </gpsramp>
    <stnlist>
      <value></value>
      <type>STR</type>
      <help>Station list for position of GPS stations.</help>
    </stnlist>
…...
</params>
```

Remember that the generated XML file can be modified in a text editor, and we again include a help string to describe each of the parameters in the file.

We are now ready to process our stack from the HDF5 file.

3. ProcessStack.py - Applying corrections

The first stage of processing, in which the data supplied by the users is modified, is accomplished using “ProcessStack.py”. The aim of this step is to

1. Correct for stratified troposphere artifacts, either
    a. Empirically by looking at relationship between InSAR phase and DEM
    b. Using weather models through the PyAPS package
2. Estimate ramps introduced due to orbital errors, either
    a. Either empirically by fitting a predefined orbit error function to data
    b. Using dense GPS observations

All the corrections are applied consistently across the interferogram network.

For this tutorial, we only choose to empirically deramping of interferograms. Details regarding other options and the associated fields in “sbas.xml” can be found in the GIAnT user manual.

Run “ProcessStack.py”

(NOTE: The ProcessStack.py command needs to be run from the X11 windows in the Remote Desktop function of EarthKit.)

```
> pwd
/home/ubuntu/data/giant/napa/GIAnT

> ProcessStack.py
logger - INFO - GIANT Toolbox - v 1.0
logger - INFO - --------------------
<module> - INFO - Input h5file: Stack/RAW-STACK.h5
<module> - INFO - Deleting previous Stack/PROC-STACK.h5
<module> - INFO - Output h5file: Stack/PROC-STACK.h5
deramp - INFO - PROGRESS: Estimating individual ramps.
[====================== 98% ==================> ]     17s /      0s
deramp - INFO - PROGRESS: Network deramp of IFGs.
[====================== 98% ==================> ]     27s /      0s
<module> - INFO - PNG preview of Deramped images: Figs/Ramp
[======>                11%                     ]     42s /    342s
```

Outputs of “ProcessStack.py” include - a processed stack file “Stack/PROC-STACK.h5” and a directory of PNG previews of deramped interferograms “Figs/Ramp”.

```
> ls Stack
PROC-STACK.h5 RAW-STACK.h5
```

To preview the contents of the new stack file

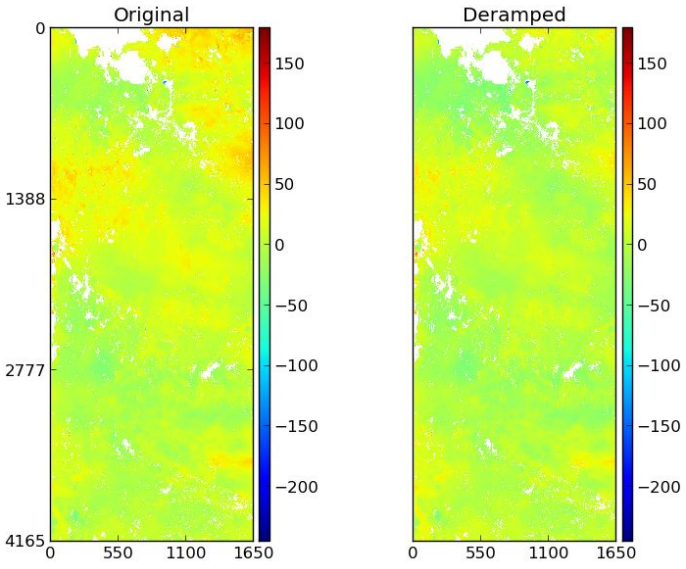
```
>h5ls Stack/PROC-STACK.h5
Jmat                     Dataset {30, 12}
bperp                    Dataset {30}
cmask                    Dataset {4165, 1650}
dates                    Dataset {12}
figram                   Dataset {30, 4165, 1650}
ramp                     Dataset {30, 3}
tims                     Dataset {12}
```

To view the contents of the directory with the PNG previews.

```
> ls Figs/Ramp
I001.png  I006.png  I011.png  I016.png  I021.png  I026.png
I002.png  I007.png  I012.png  I017.png  I022.png  I027.png
.......
```

To see the effect of deramping on the 7th interferogram in the Stack: (NOTE: you need to run this from Remote Desktop for the graphical viewer)

```
> eog Figs/Ramp/I007.png
```



Our stack is now deramped and ready for the final time-series inversion.

4. SBASInvert.py - Final inversion

In this tutorial, we demonstrate the simplest time-series inversion algorithm implemented in GIAnT - the SBAS algorithm. GIAnT also implements two other algorithms in the SBAS chain - NSBASInvert.py and TimefnInvert.py. The detailed discussion on the differences between these approaches can be found in the GIAnT user manual.

The SBAS algorithm estimates the differential displacement between one SAR acquisition and the next using a simple least squares approach. Our implementation of the algorithm estimates the time-series only for the pixels that are considered coherent in all the interferograms in the entire stack.

```
> SBASInvert.py
logger - INFO - GIANT Toolbox - v 1.0
logger - INFO - ---------------------
<module> - INFO - Number of interferograms = 30
<module> - INFO - Number of unique SAR scenes = 12
<module> - INFO - Number of connected components in network: 1
Timefn - INFO - Adding 12 linear pieces (SBAS)
<module> - INFO - Output h5file: Stack/LS-PARAMS.h5
[====================== 99% ==================> ]     800s /      0s
```

“SBASInvert.py” stores the inversion results in “Stack/LS-PARAMS.h5”.

```
> h5ls Stack/LS-PARAMS.h5
bperp                    Dataset {46}
cmask                    Dataset {1920, 2118}
dates                    Dataset {17}
gamma                    Dataset {SCALAR}
ifgcnt                   Dataset {1920, 2118}
mName                    Dataset {3}
masterind                Dataset {SCALAR}
parms                    Dataset {1920, 2118, 3}
rawts                    Dataset {17, 1920, 2118}
recons                   Dataset {17, 1920, 2118}
regF                     Dataset {3}
tims                     Dataset {17}
```

Note that the HDF5 file contains the raw time-series estimates (rawts) as well as the filtered time-series estimates (recons). In the next couple of sections, we will describe the visualization tools that are included with GIAnT.

5. plotts.py - Interactive visualization

GIAnT includes a script called “plotts.py” for interactive visualization of the generated time-series products. “plotts.py” requires a graphical desktop to run. It may require you to adjust matplotlib settings to work with an X-windows environment.

Note: (Execute Only if you have trouble using the visualization scripts)
To set matplotlib to run successfully in X-windows, edit or create this file:

```
> nano ~/.matplotlib/matplotlibrc
```

and set this value:

```
backend : TkAgg
```

(or)
Execute this on the command line

```
> echo “backend : TkAgg” >> ~/.matplotlib/matplotlibrc
```

Now we are ready to run “plotts.py”. Running the script the “-h” option list all the input parameters that can be controlled from command line.

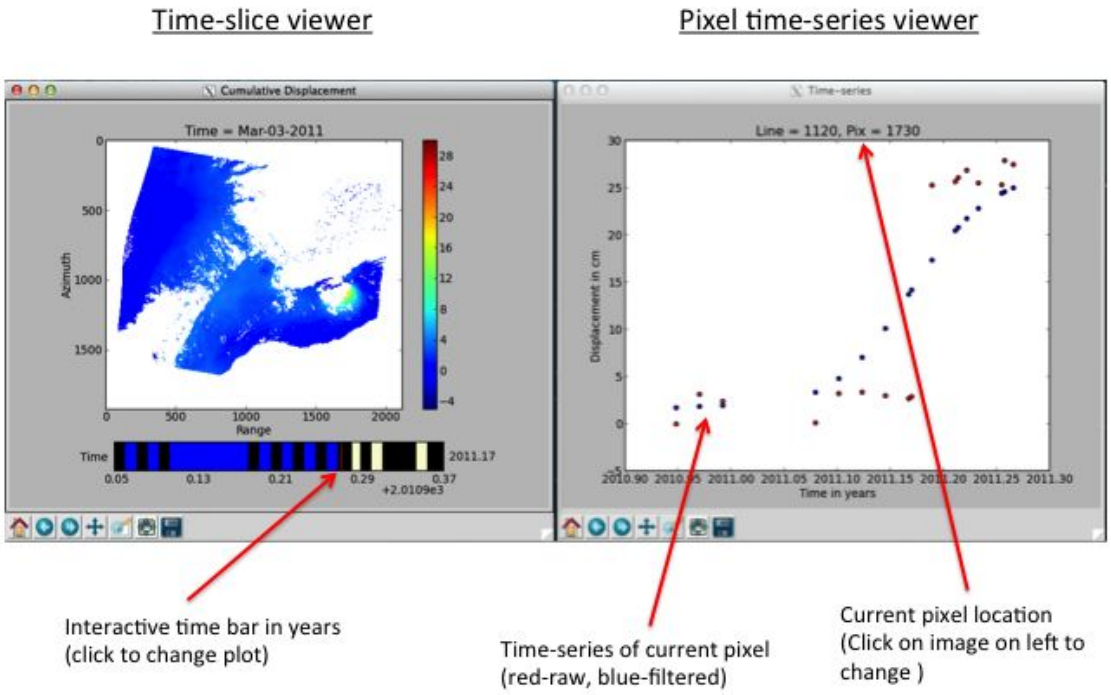
```
> plotts.py -h
logger - INFO - GIANT Toolbox - v 1.0
logger - INFO - ---------------------
usage: plotts.py [-h] [-e] [-f FNAME] [-i TIND] [-m MULT] [-y YLIM
YLIM]
                 [-ms MSIZE] [-raw] [-model] [-mask MASK MASK] [-zf]

Interactive SBAS time-series viewer

optional arguments:
  -h, --help       show this help message and exit
  -e               Display error bars if available. Default: False
  -f FNAME         Filename to use. Default: Stack/LS-PARAMS.h5
  -i TIND          Slice to display. Default: Middle index
  -m MULT          Scaling factor. Default: 0.1 for mm to cm
  -y YLIM YLIM     Y Limits for plotting. Default: [-25,25]
  -ms MSIZE        Marker size. Reduce if error bars are too small.
Default: 5
  -raw             Plot Un-Filtered Time Series as well, if available
  -model           Plot the individual model components as well. For
NSBAS, Timefn and MInTS.
```

```
  -mask MASK MASK  To mask out values. Need to provide 2 inputs -
Mask file in
                   float and xml file with dimensions. Default: None
  -zf              Changes time-origin to first acquisition for
showing time-
                   series.
```

To visualize the output from “SBASInvert.py”,

```
> plotts.py -f Stack/LS-PARAMS.h5 -y -5 30 -raw
```

This will open two plot windows - an interactive time-slice viewer and a pixel time-series viewer as shown below. The colorbar for the slice viewer ranges from -5 to 30 cm, and the raw time-series (red dots) is also shown along with the filtered time-series (blue); as requested using the command line flags -y and -raw.



Users can now view different time-slices by clicking on the time-bar and can view the time-series for different pixels by directly clicking on the pixel of interest in the image.

Some observations:

1. Our analysis clearly captures the offset associated with the Aug 24, 2014 Napa EQ.
2. GIAnT implements a simple Gaussian weighted moving average filter. Hence, the discrepancy between the raw displacement observations (red pixels) and the filtered observations (blue pixels).

3. Users can implement their own custom filtering with the raw time-series included in the HDF5 file.

Besides plotts.py, GIAnT can also export results as a movie through the “make_movie.py” script and as a Google Earth ready KML using “make_kml.py” scripts. For details and usage, refer to the GIAnT user manual. GIAnT also includes tools to export these datasets into GMT’s netcdf format and a GDAL compatible VRT. Users are strongly encouraged to use GDAL python bindings to export arrays from GIAnT’s HDF5 files to GIS-ready formats.

5. TimefnInvert.py - GPS-like time series modeling

In this section, we demonstrate the usage of “TimefnInvert.py” to perform a GPS-like functional form driven analysis of InSAR data . In this case, we define a functional form for the expected spatio-temporal evolution of the surface deformation over our area of interest based on *apriori knowledge* or observed deformation from a spatially sparse GPS network over the area of interest. For our example, we know than an earthquake occurred on Aug 24, 2014 in Napa and that our stack spans the event. We communicate a simple functional form for deformation - constant velocity + step function using a functionan named “timedict” in the “userfn.py” script as follows:

```
> less userfn.py
…
def timedict():
    rep = [['POLY',[1],[0.0]],
        ['STEP', [5.5113]]]
    return rep
```

Note that the time tags in the functional form is defined w.r.t to the first SAR acquisition in the stack (20090218) in fractional years.

```
>TimefnInvert.py
Timefn - INFO - Adding order 0 at T = 0.000000
Timefn - INFO - Adding order 1 at T = 0.000000
Timefn - INFO - Adding Step at T = 5.511300
<module> - INFO - Output h5file: Stack/TS-PARAMS.h5
[====================== 99% ==================> ]     800s /      0s
```

To visualize the results:

```
> plotts.py -f Stack/TS-PARAMS.h5 -y -15 15 -model
```

The model parameters are stored in a 3D matrix called “parms” in the output file “TS-PARAMS.h5”, and can be directly used for modeling. This should open three display windows instead of the usual two. The map of the model parameters is displayed in the third window (not linked to Pixel time-series viewer).

Note:
GIAnT user manual describes the convention for setting up complicated functional forms in detail.