mGstat

Ed. version 0.99

COLLABORATORS

	TITLE : mGstat		
ACTION	*NAME*	*DATE*	*SIGNATURE*
WRITTEN BY	Thomas Mejer Hansen	January 6, 2011	

REVISION HISTORY

NUMBER	DATE	DESCRIPTION	NAME

Contents

List of Tables

Abstract

mGstat is a geostatistical Matlab toolbox. Both native functions and interfaces to GSTAT, VISIM(GSLIB), SNESIM, and S-GeMS are provided

Chapter 1

Installation

1.1 mGstat

The latest version of mGstat is available from Sourceforge.net.

Unpacking the downloaded file as

```
cd /home/tmh/matlab
tar xvfz mgstat-0.99.tgz
```

will create a directory structure called ’mGstat’. To use the toolbox from Matlab, simply add the path where mGstat is installed to the Matlab path as

```
>> addpath /home/tmh/matlab/mGstat
>> addpath /home/tmh/matlab/mGstat/visim
>> addpath /home/tmh/matlab/mGstat/snesim
>> addpath /home/tmh/matlab/mGstat/sgems
>> addpath /home/tmh/matlab/mGstat/misc
>> addpath /home/tmh/matlab/mGstat/fast
```

The above paths can also be set running “mgstat_set_path”.

See the Matlab documentation for instructions on how to permanently add the paths to the mGstat toolbox. In Windows this can be done using the `pathtool`

1.1.1 System Requirements

mGstat is implemented using Matlab R2009b.

An effort has been made to ensure that the toolbox works with Octave version 3.2.4 (download). Octave is a free alternative to Matlab. Note however that Matlab is the main tool for development.

mGstat should work on any operating system running Matlab or Octave. However, interfaces GSTAT ([?title]), S-GeMS ([?title]), VISIM ([?title]), SNESIM ([?title]), and nfd (“FAST/nfd functions”), rely on the compilation of the related software on a specific operating system.

1.1.2 mGstat from SVN

The latest development version of mGstat can be obtain from an SVN (Subversion) repository, which can be checked out using the following command:

```
svn co https://mgstat.svn.sourceforge.net/svnroot/mgstat/trunk mgstat
```

The repository can also be browsed at SourceForge.

1.2 Extras

In addition to the native matlab geostatistical commands, mGstat contains interfaces to GSTAT ([?title]), S-GeMS ([?title]), VISIM ([?title]), SNESIM ([?title]), and nfd ("FAST/nfd functions").

As of version 0.9, mGstat includes compiled windows binaries for, GSTAT, VISIM and SNESIM. Source and compiled windows version of S-GeMS is available online (see below).

For unix systems, GSTAT, VISIM, SNESIM, and nfd must be compiled from scratch. The windows exe-file for %sgems; can optionally be run on Linux/OSX using WINE. mGstat includes source code for VISIM and SNESIM. Source code for GSTAT, S-GeMS, and nfd can be downloaded online (see below). Note that all programs but nfd is released under open source licences.

1.2.1 GSTAT

As of version 0.8, mGstat comes with a gstat.exe pre-compiled for Windows, and thus no further installation should be necessary.

As of version 1.0, mGstat comes with a pre-compiled binary for Intel Mac `gstat_mac_g3`, and thus no further installation should be necessary.

From the GSTAT website (http://www.gstat.org/) both source and binary packages can be downloaded.

The GSTAT PDF manual is a very useful source of information to have access to while using GSTAT.

1.2.1.1 Making GSTAT available for mGstat

mGstat use the m-file `gstat_binary` to locate the GSTAT binary file. `gstat_binary` searches the system path to find a binary executable called `gstat`, and chooses the first it encounters. In the `mGstat/bin` directory is also scanned.

Simply running from within Matlab should return the full path to the GSTAT binary as

```
>> gstat_binary

ans =

/usr/local/bin/gstat
```

If the gstat binary file is not in the system path, or if you have difficulties using the default automatic localization, `gstat_binary.m` can be manually edited to point to a specific location. Simple replace

```
gstat = '';
```

with

```
gstat='/usr/local/bin/gstat';
```

1.2.2 VISIM

As of version 0.8, mGstat comes with a visim.exe pre-compiled for Windows. Therefore no further installation should be necessary on Windows.

As of version 0.9, the source code for VISIM is part of the mGstat code. The source code is located in `mGstat/visim/visim/src`

To compile visim ;

```
cd mGstat/visim/visim/src/gslib
# EDIT Makefile to point to your fortran 77 or fortran 90 compiler
make
cd mGstat/visim/visim/src
# EDIT Makefile to point to your fortran 77 or fortran 90 compiler
# EDIT visim.inc to change/set the maximum array sized
make
```

this should create a binary ’visim’ or ’visim.exe’ (windows). Copy this file to

```
cp mGstat/visim/visim/src/visim mGstat/bin/.
```

A detailed manual for VISIM can be obtained from Inverse modeling and geostatistics project.

1.2.3 SNESIM

As of version 0.9, mGstat comes with a snesim.exe pre-compiled for Windows. Therefore no further installation should be necessary on Windows.

As of version 0.9, the source code for VISIM is part of the mGstat code. The source code is located in `mGstat/visim/visim/src`

1.2.4 S-GeMS

S-GeMS source, and compiled windows exe files, can be downloaded from http://sgems.sourceforge.net/. S-GeMS version 2.1 is supported by mGstat (http://downloads.sourceforge.net/sgems/sgems-2.1_installer.exe).

On windows systems the S-GeMS binary is assumed to be located in `c:\Program Files\SGeMS\sgems.exe`. If it is located on another location, it should be manually set in “sgems”.

On Linux, mGstat can call both a natively compiled S-GeMS binary and the Windows compiled S-GeMS binary using WINE

1.2.4.1 Setting the system environment variable for S-GeMS.

In order to call S-GeMS from within Matlab the environment variable `GSTLAPPLI` must be set and point to the installation directory for S-GeMS.

Using linux and the bash shell use:

```
export GSTLAPPLI=/path/to/sgems_dir
```

Using windows Vista, right click on ’My Computer’; select properties; sleect Advanced System Setting; Choose ’environment variables’;

Using windows XP, right click on ’My Computer’; select ’Properties’; select the ’Advanced’ tab; click ’Environment Variables’;

Click ’New’ to add a system variable called `GSTLAPPLI` and set to the value `/path/to/sgems_dir`

1.2.4.2 Compiling S-GeMS for Linux.

A guide for compiling S-GeMS from source code on Ubuntu Linux is available here: http://imgp.imm.dtu.dk/compile_sgems.php.

1.2.4.3 Running S-GeMS using WINE.

If you fail to compile S-GeMS natively, you can run the windows binary EXE through using operating systems supported by WINE. WINE allow running windows applications on Linux, BSD, Solaris and Mac OS X. SGeMS seems to work fine using WINE

Start by installing wine, which is available as a package for most Linux systems (for Debian/Ubuntu use):

```
sudo apt-get install wine
```

Then install the S-GeMS windows executable (download from http://downloads.sourceforge.net/sgems/sgems-2.1_installer.exe.) using WINE:

```
wine sgems-2.1_installer.exe
```

This should create desktop icon for S-GeMS (running through wine).

To use S-GeMS through WINE edit `sgems.m` to make make sure the `use_wine_on_unix` set to '1': or set a system environmental variable as:

```
setenv('USE_WINE_ON_UNIX','1')
```

1.3 Global settings

A number of environment variables can be set to control the behaviour of mGstat. The environment variable can be set in the operating system, or directly through Matlab using:

```
setenv('ENV_VAR_NAME','ENV_VAR_VALUE');
```

1.3.1 MGSTAT_VERBOSE_LEVEL

The amount of information printed to the screen when using mGstat can be controlled by the setting the `MGSTAT_VERBOSE_LEVEL`. By default it is set to

```
setenv('MGSTAT_VERBOSE_LEVEL','1')
```

A higher number increase, while a smaller number reduce the information printed to screen.

1.3.2 SEMIVAR_DEF

There are different definitions of semivariogram models. To make use of the definions used by GSTAT and S-GeMS (and GSLIB) set the following:

```
setenv('SEMIVAR_DEF','GSTAT')
setenv('SEMIVAR_DEF','SGeMS')
```

The default is to use SGeMS definitions. See also “Modeling spatial correlation”.

1.3.3 GSTLAPPLIHOME

The installation directory of S-GeMS can be given by the variable: `GSTLAPPLIHOME` This is used to find the executable file for launching S-GeMS.

1.3.4 SGEMS_DEV

If you are using the development version of S-GeMS you should set this variable to 1:

```
setenv('SGEMS_DEV','1')
```

The default option is to you the stable version of S-GeMS, and then this variable does not have to be set.

Note that mGstat may not yet support the latest development version of S-GeMS, so it is not recommended to use the development version for normal users.

Chapter 2

Native Matlab kriging algorithms

This chapter discuss how to run a number of kriging algorithms implemented natively in Matlab.

These algorithms are note fast, but may be useful for smaller problems, and for teaching purposes. For larger scale problems consider using the Matlab interfaces to GSTAT ([?title]) and S-GeMS ([?title]).

2.1 Specifications of data locations

A point in mGstat can be multidimensional (higher than 3 dimensions). Only the native Matlab implementations of geostatistical algorithm can handle this. GSTAT and GSLIB are restricted to 3D.

A point is given by a 1-row vector, where the number of columns definexs the dimension. For example, the location of the three 1D-points *(x1,x2,x3)*= *(1,5,10)* is given by

```
>> pos=[1;5;10];
>> [ndata,ndim]=size(pos)

ndata =
     3

ndim =
     1
```

More than one location is specified by a matrix where each row defines one point, and the number of rows is the number of locations. For example, the three 4-dimensional points, *(2,2,4,8)*, *(1,2,3,4)*, *(6,6,2,2)* is given by

```
>> pos=[2 2 4 8; 1 2 3 4; 6 6 2 2];
>> [ndata,ndim]=size(pos)

ndata =
     3

ndim =
     4
```

To transform locations from array structures to the matrix shape used by mGstat is straightforward in Matlab. The following two arrays denoting x and y locations

```
x =[ 1      2      3
     1      2      3];

y =[ 4      4      4
     5      5      5];
```

can be converted to the format required by mGstat by

```
>> pos=[x(:) y(:)]
pos =
     1     4
     1     5
     2     4
     2     5
     3     4
     3     5

>> [ndata,ndim]=size(pos)
ndata =
     6

ndim =
     2
```

2.2 Modeling spatial correlation

2.2.1 Semivariogram specification

Semivariogram models are specified using the GSTAT notation. For example a Spherical semivariogram model with a range of 1 and a sill of 0.1 is specified as

```
V = '0.1 Sph(1)'
```

Nested semivariogram models are specified as for example:

```
V= '0.1 Nug(0) + 0.1 Sph(1)'
```

2D anisotropy is specified as the angle of the primary direction clockwise from North, `rotation`, and the fraction of range of the range in the secondary direction (perpendicular to tha primary direction) to the range of the primary direction, `anisotro-py_factor`:

```
V = 'sill Sph(range,rotation,anisotropy_factor)'
```

To specify an angle of 30 degrees from north and a fraction of 0.3 :

```
V = '0.1 Sph(1,30,.3)'
```

See more details in the GSTAT manual.

Internally in Matlab the string describing the semivariogram model is translated into a Matlab structure. There is significant computational improvements by doing this conversion, and it allows an easier way to set semivariogram parameters from Matlab. Converting a semivariogram from string format a Matlab structure can be done using “deformat_variogram”:

```
V = deformat_variogram('0.1 Sph(1,30,.3)')
V =
     par1: 0.1000
     par2: [1 30 0.3000]
     type: 'Sph'
    itype: 1
```

The semivariogram in form of the Matlab structure is also much easier to manipulate.

To convert a semivariogram in form of a Matlab structure back into a readable string using “format_variogram”:

```
format_variogram(V,1)
ans =
0.1 Sph(1,30,0.3)
```

2.2.2 Synthetic semivariogram

A synthetic semivariogram can be calculated using `semivar_synth`, “semivar_synth”:

```
V='0.1 Nug(0) + 1 Gau(1.5)';
[sv,d]=semivar_synth(,[0:.1:6]);
plot(d,sv)
```

Note that there are different conventions for the definition of som semivariogram models. GSLIB and S-GeMS use on convention, while for example GSTAT use another. Default mGstat make use of the definitions used in mGstat. To change this see “SEMIVAR_DEF”.

2.2.3 Experimental semivariogram

There are two ways to calculate the experimental semivariogram. A native matlab function and a wrapper to GSTAT. The native matlab function allows use of multidimensional data, while the GSTAT wrapper only allows up to 3D data observations. The native Matlab function allows computation of several angle ranges at once while the GSLIB wrapper must be called separately for each angle array. However, the GSLIB wrapper is much faster.

2.2.3.1 Native Matlab

“semivar_exp” is a native Matlab function to compute directional dependent experimental semivariograms from multi dimensional data observations. An example assuming an isotropic semivariogram model:

```
[gamma,h]=semivar_exp(pos,val);
plot(h,gamma);
```

The semivariogram in a number of angle ranges can be simultaneously calculated using:

```
% Example directional [0,45,90,135,180]:
[gamma,h,angle_center]=semivar_exp(pos,val,20,4);
plot(h,gamma);
legend(num2str(angle_center))
```

This computes the semivariogram in for angle arrays, from 0-45, 45-90, 90-135, 135-380. ’angle_center’ is the the center of each angle gather : 22.5, 67.5, 112.5, 157.6 degrees.

The angle range can manually be specified using:

```
% Example directional [0,45,90,135,180]:
ang=[0 45 90 135 180];
[gamma,h,angle_center]=semivar_exp(pos,val,20,4);
plot(h,gamma);
legend(num2str(angle_center))
```

The semivariogram for angles between for example 13 and 22 degrees, can be computed using :

```
% Example directional 13-22 deg
[gamma,h,angle_center]=semivar_exp(pos,val,20,[13 22]);
plot(h,gamma);
legend(num2str(angle_center))
```

2.2.3.2 GSTAT

“semivar_exp_gstat” is a wrapper for GSTAT for computing the directional dependent experimental semivariogram for one angle range. Is supports up to three dimensional data observations. The angle range is specified as the angle and a tolerance. Thus the semivariogram in within the angle range 20 +-10 degrees is found using :

```
[gamma,h]=semivar_exp_gstat(pos,val,20,10)
```

2.3 Estimation

Multidimensional kriging estimation with noisy data observations can be performed using “krig”

```
[d_est,d_var,lambda_sk,K_dd,k_du,inhood]=krig(pos_known,val_known,pos_est,V,options);


ndata : number of data observations
ndims : dimensions of data location (>=1)
nest  : number of data locations to be estimated

pos_known [ndata,ndims] : Locations of data observations
val_known [ndata,1 or 2]  : col1 : Data value as measured at 'pos_known'
                            col2 : Data uncertainty as measured at
'pos_known' (optional)
pos_est   [1 ,ndims] : Location of data to be estimated
V : Variogram model, e.g. '1 Sph(100)'
options : kriging options.
```

Please note data uncertainty is listed as the second column of `val_known`. Data uncertainty is defined as the variance of Gaussian noise distribution associated to each data measurement. Specified in this manner, the noise on data observations is considered uncorrelated. If only one column is specified, data observations are treated as noise free.

2.3.1 Kriging Options

`options`, the last argument, is a Matlab structure that controls most aspect of the kriging, such as choosing the neighborhood, and kriging method. The names for most of these options are same as the names used to control GSTAT, see [?title]

2.3.1.1 kriging methods

the Kriging methods: simple Kriging, ordinary Kriging and Kriging with a trend are all available using `krig`. The difference between these three methods is the way the trend is modelled. Simple Kriging assumed a constant and known mean. Ordinary kriging makes use of an varying unknown mean (that is estimated within the neighborhood). Kriging with a trend model the trend as a smoothly varying polynomial trend. Thus ordinary kriging is but a form of kriging with a trend,; a 0th order polynomial trend.

2.3.1.1.1 Simple kriging

By default ordinary Kriging in an exhaustive neighborhood (i.e. all data measurements are used all the time) is performed. This is identical to simple Kriging when `options.mean=mean(pos_known(:,1))`

2.3.1.1.2 Ordinary kriging

If the 'mean' is given as `options.mean`, Simple Kriging is performed.

2.3.1.1.3 Kriging with a trend / Universal kriging

For each dimension (direction) the order of the polynomial fit of the trend can be specified by `options.polyfit`

if the value of `options.polyfit` is an integer scalar, then the same polynomial fit is used for all dimensions. Thus the default linear trend in all directions is identical to specifying `options.polyfit=1`.

if the value of `options.polyfit` is an array of integers, each integer in the array must specify the order of the trend for each dimension. The length of the array must be equal to the size of the dimension of the observation. Thus, for 2D data observations one can specify a 2nd order polynomial trend in the first direction and a 0th order fit in the second direction as `options.polyfit=[2 0]`.

option.[?]	**GSTAT equiv**	**description**	**link**
sk_mean,mean	sk_mean	Specify the global mean, as used by simple kriging	
trend	trend	Krig only the trend.	
max	max	The maximum number of data to use in the search neighborhood	
polytrend	d	The polynomial order of the trend for each dimension	
xvalid	xvalid	If specified as `xvalid=1` cross validation on known data locations is performed	
isorange		`isorange=1` assumes no rotation in anisotropy. If chosen, each entry in the range section of a variogram corresponds to the range for a certain dimension. For example 'Sph(1,10,1,100)' corresponds to a range of 1 in the first dimension, 10 in the second dimension, 1 in the third dimension and 100 in the fourth dimension. If GSTAT is used for kriging in 1, 2 and 3 dimensions, the range selections are translates properly to GSTAT format using the isorange function.	

Table 2.1: kriging options

2.3.1.2 kriging neighborhood

By default all data observations are always used. The kriging neighborhood denote the data that are actually used by the kriging systems.

A maximum number of data used by the kriging system is selected as `options.max=10`. The data locations closes to the point being estimated is retained in the data neighborhood.

See also “nhood” that controls the data neighborhood behavior.

2.3.2 Kriging examples

Based on the data observations below, a number of example are shown illustrating the use of kriging in mGstat

2.3.2.1 1D Kriging, no data uncertainty

In the following example 3 data measurements has been made : x(1)=0; x(5)=3; x(2)=2. Using a Spherical semivariogram model with a range of ’0.2’ and a sill of ’1’, the mean and variance of the distribution of the local probability density function at x(2) is found:

```
pos_known=[1;5;10];
val_known=[0;3;2]; % adding some uncertainty
V='1 Sph(.2)';      % Select variogram model
pos_est=[2]';
[d_est,d_var]=krig(pos_known,val_known,pos_est,V)


d_est =

    1.6667


d_var =

    1.3333
```

from: `mGstat/examples/mgstat_examples/krig_ex1.m`

2.3.2.2 Kriging a series of points - noise free data

```
pos_known=[1;5;10];
val_known=[0;3;2]; %
V='1 Sph(.2)';      % Select variogram model
pos_est=[0:.1:10]';
[d_est,d_var]=krig(pos_known,val_known,pos_est,V);
plot(pos_est,d_est,'k',pos_known,val_known,'ro')
print -dpng krigex2
```

2.3.2.3 Kriging a series of point - SK, OK, Ktrend

```
pos_known=[1;5;10]; %
val_known=[0;3;2];  %
V='1 Sph(.2)';      % Select variogram model
pos_est=[0:.1:10]';
[d_est_ok,d_var_ok]=krig(pos_known,val_known,pos_est,V);
options.mean=2;
```

```
[d_est_sk,d_var_sk]=krig(pos_known,val_known,pos_est,V,options);
options.trend=1;
[d_est_kt,d_var_kt]=krig(pos_known,val_known,pos_est,V,options);
plot(pos_est,[d_est_sk,d_est_ok,d_est_kt],'-',pos_known,val_known,'ro')
legend('SK','OK','KT','Data')
print -dpng krigex3
```

2.3.2.4 Kriging a series of point - SK, OK, Ktrend

```
rand('seed',1)
ndata=10;
pos_known=rand(ndata,1)*10;
val_known=randn(ndata,1); %
V='1 Sph(.2)';      % Select variogram model
pos_est=[0:.1:10]';
clear options;
[d_est_ok,d_var_ok]=krig(pos_known,val_known,pos_est,V,options);
options.mean=2;
[d_est_sk,d_var_sk]=krig(pos_known,val_known,pos_est,V,options);
options.trend=1;
[d_est_kt,d_var_kt]=krig(pos_known,val_known,pos_est,V,options);
plot(pos_est,[d_est_sk,d_est_ok,d_est_kt],'-',pos_known,val_known,'k*')
legend('SK','OK','KT','Data')
print -dpng krigex4
```

2.3.2.5 Kriging a series of point - SK, OK, Ktrend - Neighborhood

```
rand('seed',1)
ndata=10;
pos_known=rand(ndata,1)*10;
val_known=randn(ndata,1); %
V='1 Sph(.2)';      % Select variogram model
pos_est=[0:.1:10]';
clear options;options.max=4;
[d_est_ok,d_var_ok]=krig(pos_known,val_known,pos_est,V,options);
options.mean=2;
[d_est_sk,d_var_sk]=krig(pos_known,val_known,pos_est,V,options);
options.trend=1;
[d_est_kt,d_var_kt]=krig(pos_known,val_known,pos_est,V,options);
plot(pos_est,[d_est_sk,d_est_ok,d_est_kt],'-',pos_known,val_known,'k*')
legend('SK','OK','KT','Data')
print -dpng krigex5
```

2.3.2.6 Kriging a series of point - SK, OK, Ktrend - Neighborhood, noisy data

```
rand('seed',1)
ndata=30;
pos_known=rand(ndata,1)*10;
val_known=randn(ndata,1); %
val_var=zeros(ndata,1)+.1; %
V='1 Sph(.1)';      % Select variogram model
pos_est=[-2:.1:12]';
clear options;options.max=4;
[d_est_ok,d_var_ok]=krig(pos_known,[val_known val_var],pos_est,V,options);
options.mean=mean(val_known);
[d_est_sk,d_var_sk]=krig(pos_known,[val_known val_var],pos_est,V,options);
```

```
options.trend=1;
[d_est_kt,d_var_kt]=krig(pos_known,[val_known val_var],pos_est,V,options);
plot(pos_est,[d_est_sk,d_est_ok,d_est_kt],'-',pos_known,val_known,'k*')
legend('SK','OK','KT','Data')
print -dpng krigex6
```

2.4 Simulation

can be used to perform sequential Gaussian simulation using the same arguments as “krig”. Only extra options is that the number of realizations computed can be set using

```
options.nsim = 10;
```

Chapter 3

GSTAT from Matlab

This chapter discuss how to run GSTAT from within Matlab.

3.1 Working with GSTAT and mGstat

3.1.1 The GSTAT parameter file in mGstat

GSTAT can be run non-interactively using by parsing a parameter file. It is by reading and writing this printer file that mGstat interfaces with GSTAT. Consider the following GSTAT parameter file

```
#
# Local simple point kriging on a mask map
#
data(ln_zinc): 'zinc.eas', x=1, y=2, v=3, log,
  min=20, max=40, radius=1000, sk_mean=5.9;
variogram(ln_zinc): 0.0554 Nug(0) + 0.581 Sph(900);
mask:                 'mask_map';
predictions(ln_zinc): 'lzn_skpr';
variances(ln_zinc):   'lzn_skvr';
```

using read_gstat_par to read the parameter into the data structure G, gives

```
>> G=read_gstat_par(par)
G =
         mgstat: [1x1 struct]
           data: {[1x1 struct]}
      variogram: {[1x1 struct]}
           mask: {[1x1 struct]}
    predictions: {[1x1 struct]}
      variances: {[1x1 struct]}

>> G.mgstat
ans =
    parfile: '/home/tmh/RESEARCH/PROGRAMMING/gstat-2.4.4/cmd/ex05.cmd'
    comment: {'#'  '#Local simple point kriging on a mask map'  '#'}

>> G.data{1}
ans =
       data: 'ln_zinc'
       file: 'zinc.eas'
          x: 1
          y: 2
          v: 3
        log: ''
        min: 20
        max: 40
     radius: 1000
    sk_mean: 5.9000

>> G.predictions{1}
ans =
    data: 'ln_zinc'
    file: 'lzn_skpr'
```

The mgstat field to the G structure, is specific to mGstat and stores the comments of the parameter file, and the location on disk of the parameter file.

The rest of the fields of G refers to lines in the GSTAT parameter file.

3.1.1.1 'data' field of GSTAT parameter file

Take for example the data field as listed above. The field is called data, because this is the identifier (first string) in the parameter file. Filename and data identifiers are always specified using 'data' and 'file' fields. Several options can be specified for the 'data'. This are simply listed as fields of G.data{1}. If an option does not supply a value (as the 'log' option) it simply refers to an empty string.

In case several data type are listed in the parameter file, they are read into separate structures, as G.data{1}, G.data{2} ,...

3.1.2 An interactive GSTAT session in Matlab

to come

3.2 GSTAT-related m-files

3.2.1 gstat

gstat is used to call gstat from within Matlab. It can be called using either a GSTAT command file as :

```
[pred_mean,pred_var]=gstat('ex06.cmd');
```

or using a Matlab mGstat structure as

```
G=read_gstat_par('ex06.cmd');       % read parameter file
G.G.variogram{1}.V(1).type='Sph';   % change variogram type to Spherical
[pred_mean,pred_var]=gstat(G);
```

More info at : Section 8.1.28

3.2.1.1 output precision

By default the output precision of GSTAT is set to format '%16.8f'. This can be specified manually as :

```
G.set.format='%4.2f'
```

3.2.2 gstat_read_par

More info at : Section 8.1.79

3.2.3 gstat_write_par

More info at : Section 8.1.106

3.2.4 gstat_krig

`gstat_krig` is the equivalent of the native Matlab command `krig`. It is called in similar fashion to `krig`, but calls GSTAT for kriging as opposed to the Matlab kriging routines.

More info at : Section 8.1.31

3.2.5 gstat_convert

Converts binary formatted data formats to ascii.

More info at : Section 8.1.30 and Section 1.2.1.1

3.2.6 gstat_binary

More info at : Section 8.1.29

3.2.7 semivar_exp_gstat

NB: In the forthcoming releases this m-file will be rename `gstat_semivar_exp`

This m-file computes the experimental semivariogram using the same conventions as Section 8.1.88, but using GSTAT as backend instead of the native Matlab implemention.

Section 8.1.89 is much more CPU efficient that Section 8.1.88.

An example (from MGSTAT_INSTALL/example/test_gstat_semivar_exp.m)

```
% GENERATE A REFERENCE DATA SET USING UNCONDITIONAL GAUSSIAN SIMULATION
x=[0:.05:10];
y=[0:.05:10];
V=visim_init(x,y);
V.rseed=1;
V.Va.a_hmax=4; % maximum correlation length
V.Va.a_hmin=.5;  % minumum correlation length
V.Va.ang1=90-22.5;   % Rotation angle of dip(clockwise from north)
V.Va.it=1;     % Gaussian semivariogram
V=visim(V);    % run visim;

[x_obs,y_obs]=meshgrid(x,y);
d_obs=V.D(:,:,1);
n_obs=prod(size(d_obs));


% CHOOSE SOME DATA FOR SEMIVARIOGRAM ANALYSIS
n_use=1000;
i_use=round(rand(1,n_use)*(n_obs-1))+1;
i_use=unique(i_use);

x_use=x_obs(i_use);
y_use=y_obs(i_use);
d_use=d_obs(i_use);

% PLOT DATA
figure(1);
```

```
imagesc(V.x,V.y,V.D(:,:,1));
title(visim_format_variogram(V))
axis image;
hold on
plot(x_use,y_use,'w.','MarkerSize',22)
scatter(x_use,y_use,20,d_use,'filled')
hold off
drawnow;

% SEMIVARIOGRAM ANALYSIS ISOTROPIC
[gamma_iso,hc,np,av_dist]=semivar_exp_gstat([x_use(:) y_use(:)],[d_use(:)]);
figure(2);
plot(hc,gamma_iso);
title('isotropic');xlabel('Distance');ylabel('\gamma')

% SEMIVARIOGRAM ANALYSIS ANISOTROPIC
ang_array=[0,22.5,45,67.5,90];
ang_tolerance=10;
for i_ang=1:length(ang_array);
    [gamma_an(:,i_ang),hc,np,av_dist]=semivar_exp_gstat([x_use(:) y_use(:)],[d_use(:)], ↩
        ang_array(i_ang),ang_tolerance);
end
figure(3);
plot(hc,gamma_an);xlabel('Distance');ylabel('\gamma')
title('ANisotropic');
legend(num2str(ang_array'))

% SYNTHETICAL SEMIVARIOGRAM
gamma_synth=semivar_synth('0.0001 Nug(0) + 1 Sph(1)',hc);
figure(4)
plot(hc,gamma_an,'b-')
hold on
plot(hc,gamma_iso,'r-','linewidth',2)
plot(hc,gamma_synth,'k-','linewidth',2)
hold off
;xlabel('Distance');ylabel('\gamma')
legend(num2str(ang_array'))
```

More info at : Section 8.1.89

3.3 GSTAT examples

3.3.1 GSTAT ex03

```
% ex03 : gstat example ex03.cmd
cmd_file='ex03';
[pred,pred_var,pred_covar,mask,G]=gstat(sprintf('%s.cmd',cmd_file));

[obs,obs_header,obs_title]=read_eas(G.data{1}.file);

figure(3);clf;
imagesc(mask.x,mask.y,pred(:,:,1));

hold on
plot(obs(:,1),obs(:,2),'k.','MarkerSize',10);
scatter(obs(:,1),obs(:,2),10,obs(:,3));
hold off
axis image
```

```
cb=colorbar;
set(get(cb,'Ylabel'),'string',obs_header{3})
title(sprintf('GSTAT %s.cmd - %s',cmd_file,obs_title))
xlabel(obs_header{1})
ylabel(obs_header{2})

print('-dpng',sprintf('%s.png',cmd_file))
```

3.3.2 GSTAT ex04

```
% ex04 : gstat example ex04.cmd
cmd_file='ex04';
[pred,pred_var,pred_covar,mask,G]=gstat(sprintf('%s.cmd',cmd_file));

[out,out_header,out_title]=read_eas(G.set.output);
[obs,obs_header,obs_title]=read_eas(G.data{1}.file);

figure(4);clf;
scatter(obs(:,1),obs(:,2),10,obs(:,3));
hold on
plot(out(:,1),out(:,2),'k.','MarkerSize',12);
scatter(out(:,1),out(:,2),10,out(:,3));
hold off
axis image
cb=colorbar;
set(get(cb,'Ylabel'),'string',obs_header{3})
title(sprintf('GSTAT %s.cmd - %s',cmd_file,obs_title))
xlabel(obs_header{1})
ylabel(obs_header{2})

print('-dpng',sprintf('%s.png',cmd_file))
```

3.3.3 GSTAT ex05

```
% ex05 : gstat example ex05.cmd
cmd_file='ex05';
[pred,pred_var,pred_covar,mask,G]=gstat(sprintf('%s.cmd',cmd_file));

[obs,obs_header,obs_title]=read_eas(G.data{1}.file);

if (isfield(G.data{1},'log')); pred=exp(pred);end

figure(5);clf;
subplot(1,2,1);
imagesc(mask.x,mask.y,pred(:,:,1));
hold on
plot(obs(:,1),obs(:,2),'k.','MarkerSize',12);
scatter(obs(:,1),obs(:,2),10,obs(:,3));
hold off
axis image
cb=colorbar;
set(get(cb,'Ylabel'),'string',obs_header{3})
xlabel(obs_header{1})
ylabel(obs_header{2})
title('Mean')

subplot(1,2,2);
imagesc(mask.x,mask.y,pred_var(:,:,1));
```

```
colorbar
hold on
plot(obs(:,1),obs(:,2),'k.','MarkerSize',12);
hold off
axis image
%cb=colorbar;
%set(get(cb,'Ylabel'),'string',obs_header{3})
xlabel(obs_header{1})
ylabel(obs_header{2})
title('Variance')

watermark(sprintf('GSTAT %s.cmd - %s',cmd_file,G.mgstat.comment{2}));

print('-dpng',sprintf('%s.png',cmd_file))
```

3.3.4 GSTAT ex06

```
% ex06 : gstat example ex06.cmd
cmd_file='ex06';
[pred,pred_var,pred_covar,mask,G]=gstat(sprintf('%s.cmd',cmd_file));
figure(6),clf;
imagesc(mask.x,mask.y,pred(:,:,1));
cb=colorbar;
axis image
title('Unconditional Gaussian simulation')
watermark(sprintf('GSTAT %s.cmd - %s',cmd_file,G.mgstat.comment{2}));

print('-dpng',sprintf('%s.png',cmd_file))
```

3.3.5 GSTAT ex07

```
% ex07 : gstat example ex07.cmd
cmd_file='ex07';
[pred,pred_var,pred_covar,mask,G]=gstat(sprintf('%s.cmd',cmd_file));


[obs,obs_header,obs_title]=read_eas(G.data{1}.file);

if (isfield(G.data{1},'log')); pred=exp(pred);end



figure(7);clf;
imagesc(mask.x,mask.y,pred(:,:,1));

hold on
plot(obs(:,1),obs(:,2),'k.','MarkerSize',12);
scatter(obs(:,1),obs(:,2),10,obs(:,3));
hold off
axis image
cb=colorbar;
set(get(cb,'Ylabel'),'string',obs_header{3})
xlabel(obs_header{1})
ylabel(obs_header{2})


cb=colorbar;
axis image
```

```
title('Unconditional Gaussian simulation')
watermark(sprintf('GSTAT %s.cmd - %s',cmd_file,G.mgstat.comment{2}));

print('-dpng',sprintf('%s.png',cmd_file))
```

3.3.6 GSTAT ex09

```
% ex09 : gstat example ex09.cmd
cmd_file='ex09';
disp(sprintf('%s : There (seems to be) a bug in GSTAT setting NCOLUMNS = 6, when there is ↩
    only 5 columes in the output EAS file',mfilename));
[pred,pred_var,pred_covar,mask,G]=gstat(sprintf('%s.cmd',cmd_file));

```

3.3.7 GSTAT ex10

```
cmd_file='ex10';
[pred,pred_var,pred_covar,mask,G]=gstat(sprintf('%s.cmd',cmd_file));


[obs1,obs_header1,obs_title1]=read_eas(G.data{1}.file);
[obs2,obs_header2,obs_title2]=read_eas(G.data{2}.file);

for i=1:2;
    if (isfield(G.data{i},'log')); pred(:,:,i)=exp(pred(:,:,i));end
end

clf;
subplot(2,2,1);
imagesc(mask.x,mask.y,pred(:,:,1));axis image;title([G.predictions{1}.data,' mean estimate' ↩
    ])
hold on
plot(obs1(:,1),obs1(:,2),'k.','MarkerSize',12);
scatter(obs1(:,1),obs1(:,2),10,obs1(:,G.data{1}.v),'filled');
hold off
axis image
cb=colorbar;
set(get(cb,'Ylabel'),'string',obs_header1{3})
xlabel(obs_header1{1})
ylabel(obs_header1{2})

subplot(2,2,2);
imagesc(mask.x,mask.y,pred(:,:,2));axis image;title([G.predictions{2}.data,' mean estimate' ↩
    ])
hold on
plot(obs2(:,1),obs2(:,2),'k.','MarkerSize',12);
scatter(obs2(:,1),obs2(:,2),10,obs1(:,G.data{2}.v),'filled');
hold off
axis image
cb=colorbar;
set(get(cb,'Ylabel'),'string',obs_header2{3})
xlabel(obs_header2{1})
ylabel(obs_header2{2})

subplot(2,2,3);
imagesc(mask.x,mask.y,pred_var(:,:,1));axis image;
colorbar
title([G.predictions{1}.data,' variance estimate'])
```

```

subplot(2,2,4);
imagesc(mask.x,mask.y,pred_var(:,:,2));axis image;
colorbar
title([G.predictions{1}.data,' variance estimate'])


watermark(sprintf('GSTAT %s.cmd - %s',cmd_file,G.mgstat.comment{2}));

print('-dpng',sprintf('%s',cmd_file))
```

Chapter 4

VISIM - Direct and Gaussian sequential simulation

This chapter discuss how to run VISIM from within Matlab.

4.1 VISIM

VISIM is a sequential simulation code based on GSLIB ('Geostatistical Software LIBrary', Stanford Center for Reservoir Forecasting, Stanford University) for sequential Gaussian and direct sequential simulation with histogram reproduction. In addition to classical simulation based on noise-free hard data of point support, VISIM also handles noisy data of mixed support, enabling linear stochastic inversion using the sequential simulation approach.

VISIM can be used to generate samples of the a posteriori distribution of a linear inverse problem.

For detailed information the usage of VISIM visit the VISIM homepage at IMGP. [user manual pdf].

References to the use of VISIM should be made to :

Hansen, T. M., and Mosegaard, K., 2008. VISIM : Sequential simulation for linear inverse problems. Computers andGeosciences, 34(1), pp 53-76. [doi:10.1016/j.cageo.2007.02.003].

4.1.1 Running VISIM from Matlab

The three main files to control VISIM from Matlab are Section 8.2.4 Section 8.2.56 Section 8.2.6

4.1.1.1 Check path to VISIM

When running Section 8.2.6 an attempt is made to look for a VISIM binary. First the 'bin' sub folder where mGstat is installed is searched, then the system path is searched for 'visim' binary file. By running Section 8.2.6 with no arguments the path to the use binary (if located) is listed:

```
visim;
Using VISIM binary : ~/bin/visim
```

If the binary for VISIM is not found you have to edit the 'visim.m' m-file and manually give set the path in the top of the file.

4.1.1.2 Running VISIM from Matlab

Section 8.2.6 is used to run VISIM from within Matlab. The input is either a VISIM parameter file (as a string) or a VISIM Matlab structure, as obtained using Section 8.2.4.

Therefore the following two approached will run VISIM on the `visim_sgsim.par`:

```
V = visim('visim_sgsim.par');
```

```
V = visim('visim_sgsim.par');
V = visim(V);
```

which will result in the following out to the screen :

```

 VISIM Version: 1.000

 filename is sgsim_uncond.par
 sgsim_uncond.par
 Initializing data2vol covar lookup table
 Initializing vol2vol covar lookup table
 Working on realization number  1
 Working on realization number  2
 Working on realization number  3
...
 Working on realization number  100

V =

                parfile: 'sgsim_uncond.par'
               cond_sim: 0
              fconddata: [1x1 struct]
                   cols: [6x1 double]
               fvolgeom: [1x1 struct]
                fvolsum: [1x1 struct]
             trimlimits: [2x1 double]
             debuglevel: -11
                    out: [1x1 struct]
                   nsim: 100
                   ccdf: 0
                refhist: [1x1 struct]
                     nx: 21
                    xmn: 0.1250
                   xsiz: 0.2500
                     ny: 49
                    ymn: 0.1250
                   ysiz: 0.2500
                     nz: 1
                    zmn: 0.1250
                   zsiz: 0.2500
                      x: [1x21 double]
                      y: [1x49 double]
                      z: 0.1250
                  rseed: 69068
                minorig: 0
                maxorig: 1
               nsimdata: 28
                  volnh: [1x1 struct]
              densitypr: 0
        assign_to_nodes: 1
    max_data_per_octant: 0
          search_radius: [1x1 struct]
          search_angle: [1x1 struct]
                 gmean: 0.1304
                  gvar: 2.0000e-04
                    Va: [1x1 struct]
                  tail: [1x1 struct]
                     D: [21x49x7 double]
                 etype: [1x1 struct]
```

The output of running visim is the Matlab structure listed above, that contains all parameters of the VISIM used parameter file, as well as the simulated/estimated data `V.D`, and the E-type mean and variance as `V.etype.mean` and `V.etype.var`

An example of running 9 runs of VISIM while changing the primary anisotropy direction from 0 to 90 is the following

```
Vorig = read_visim('visim_sgsim.par');
for i=1:4
  V{i}=Vorig;
  V{i}.Va.ang1=i*10
  V{i}=visim(V{i}));
end
```

Each of the Matlab structures `V{1}`,`V{2}`,..,`V{9}` now contain the simulation result.

4.1.2 Plotting VISIM realizations

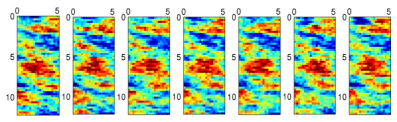
To plot a number of generated realizations use Section 8.2.6.

The simplest use of Section 8.2.6 is simple to specify a number of realizations to plot.

```
V=read_visim('sgsim_cond_1.par');
visim_plot_sim(V,2)
```

An example of using all the options available for Section 8.2.6

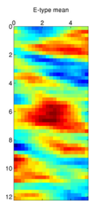
```
nsim=7;      % number of realizations to plot
cax=[.1 .16]; % scaling for colorbar axis
FS = 10;     % FontSize
nxsub=7;     % Number of subplots in the X-direction
nzsub=7;     % Number of subplots in the z-direction
visim_plot_sim(V,nsim,cax,FS,nxsub,nzsub);
```



4.1.2.1 Plotting VISIM E-type

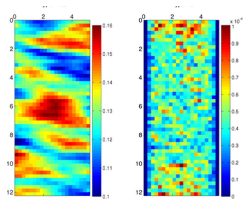
In case VISIM is run in simulation mode, `visim_plot_etype` plots the E-type (the point wise mean and/or variance) of all generated simulations.

```
cax=[.1 .16]; % scaling for colorbar axis
visim_plot_etype('sgsim_cond_1.par');
```



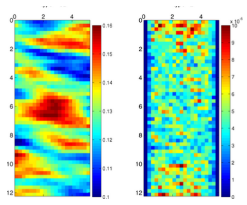
The following will plot both the E-type mean and variance.

```
V=read_visim('sgsim_cond_1.par');
plotAll=1;
visim_plot_etype(V,plotAll);
```



The following will plot both the E-type mean and variance with the specified colorscales.

```
V=read_visim('sgsim_cond_1.par');
cax=[.1 .16]; % scaling for colorbar axis E-type Mean
cax_var=[0  1e-4]; % scaling for colorbar axis E-type variance
plotAll=1;
visim_plot_etype(V,plotAll,cax,cax_var);
```

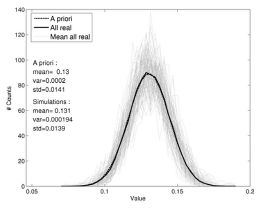


See more info at Section 8.2.20

4.1.2.2 Plotting VISIM histogram

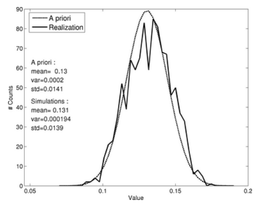
To plot the histogram for all realizations, compared to the a priori chosen one use `visim_plot_hist` :

```
V=read_visim('sgsim_uncond.par');
visim_plot_hist(V);
```



and to plot just the histogram of one simulation use

```
V=read_visim('sgsim_uncond.par');
visim_plot_hist(V,10);
```

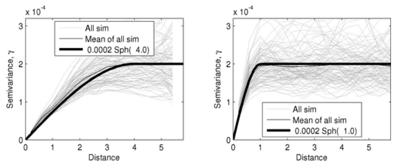


See more info at Section 8.2.21

4.1.2.3 Plotting VISIM semivariogram

To plot the experimental semivariograms compared to the a priori chosen semivariogram, use `visim_plot_semivar_real` :

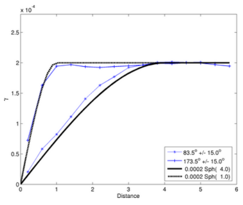
```
V=read_visim('sgsim_uncond.par');
visim_plot_semivar_real(V);
```



See more info at Section 8.2.29

To compatre the mean experiemntal computed for a number of realizatoins to the a priori chosen semivariogram, use

```
V=read_visim('sgsim_uncond.par');
visim_plot_semivar(V,1:V.nsim);
```



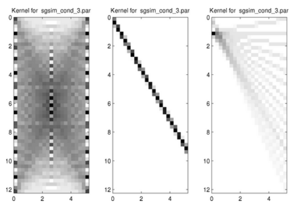
See more info at Section 8.2.25

4.1.2.4 Plotting the sensitivity kernel

The sensitivity kernel for all or a specific selection of volume average data can be plotted using :

```
subplot(1,3,1)
visim_plot_kernel('sgsim_cond_3.par');
subplot(1,3,2)
visim_plot_kernel('sgsim_cond_3.par',11);
subplot(1,3,3)
visim_plot_kernel('sgsim_cond_3.par',11:25);
colormap(1-gray)
```

This will result in the following :



See more info at Section 8.2.22

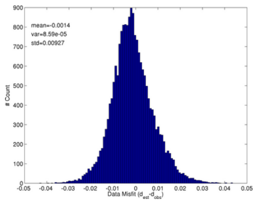
4.1.2.5 Plotting VISIM conditional lookup table

See more info at Section 8.2.19

4.1.2.6 Plotting the distribution of the prediction error of the used volume average data

To plot the distribution of the volume average estimates as calculated form the realization and the observed volume average values use:

```
V=read_visim('sgsim_cond_1.par');
visim_plot_volfit(V);
```



See more info at Section 8.2.32

4.2 VISIM examples

Here follows a few examples for problems that can be addressed using VISIM

4.2.1 visim_init

`visim_init` generate a reference data structure (equivalent of a VISIM parameter file) for unconditional simulation:

```
V=visim_init;
V=visim(V);
visim_plot_sim(V);
```

`visim_init` can optionally be called with a suggested geometry:

```
V=visim_init(1:1:50,1:2:200);
V=visim(V);
visim_plot_sim(V);
```

Finally, `visim_init` an existing VISIM structure can be passed, that will form the base of an update VISIM structure:

```
V=visim_init(1:1:50,1:2:200,V);
V=visim(V);
visim_plot_sim(V);
```

When `visim_init` is called, the gloval variance `V.gvar` is checked for consistency with the semivariogram model, and fixed appropriately such that the global variance is set to the total sill value of the specicied semivariogram. The tail values will also be checked for consistency if `V.ccdf=1`.

4.2.2 Direct Sequential Simulation

If `V.ccdf=1`, direct sequential simulation is performed. This enable the use of a non-Gaussian distribution of the subsurface parameters (the target distribution). The shape of the target distribution is given by the data found in the file`V.refhist.fn-ame`. The target distribution can be treated as either a continious or a discrete function using`V.refhist.do_discrete`.

The following example will perform unconditional simulation with a trimodal target distribution assumed to be continious:

```
V=visim_init(1:1:61,1:1:61);
V.parfile='visim_example_dssim_cont_1.par';
d1=randn(1,2000)*sqrt(.2)+8;
d2=randn(1,1200)*sqrt(.1)+10;
d3=randn(1,2800)*sqrt(.1)+13;
d_target=[d1,d2,d3]';
V.refhist.fname='dssim_target.eas';
write_eas(V.refhist.fname,d_target); % write target distribution
V.ccdf=1;                   % use DSSIM
V.refhist.do_discrete=0;   % Assume continious target histogram
V.nsim=10;
V=visim_init(V);
V.Va.it=3;     % Choose Gaussian semivariogram
V.Va.a_hmax=15; % correlation length (direction of max continuity)
V.Va.a_hmin=15; % correlation length (direction of min continuity)
V=visim(V);
figure(1);visim_plot_sim(V);
print_mul('visim_example_dssim_cont_sim');
figure(2);visim_plot_hist(V);
print_mul('visim_example_dssim_cont_hist');


```

The following example will perform unconditional simulation with a target distribution chosen as [1 10 10 40], asssmued to be continious:

```
V=visim_init(1:1:61,1:1:61);
V.parfile='visim_example_dssim_cont_2.par';
d_target=[1 10 10 40]';
V.refhist.fname='dssim_target_discrete.eas';
write_eas(V.refhist.fname,d_target); % write target distribution
V.ccdf=1;                   % use DSSIM
V.refhist.do_discrete=0;   % Assume continious target histogram
V.nsim=10;
V=visim_init(V);
V.Va.it=3;     % Choose Gaussian semivariogram
V.Va.a_hmax=15; % correlation length (direction of max continuity)
V.Va.a_hmin=15; % correlation length (direction of min continuity)
V=visim(V);

figure(1);visim_plot_sim(V);
print_mul('visim_example_dssim_cont_1_sim');
figure(2);visim_plot_hist(V);
print_mul('visim_example_dssim_cont_1_hist');


```

The last DSSIM example is a example of unconditional simulation with a target distribution chosen as [1 10 10 40], asssmued to be discrete. This means that no other values than the ones given in the target distirbution can be simulated. This can be used for categorical simulation:

```
V=visim_init(1:1:61,1:1:61);
V.parfile='visim_example_dssim_discrete_1.par';
d_target=[1 10 10 40]';
V.refhist.fname='dssim_target_discrete.eas';
write_eas(V.refhist.fname,d_target); % write target distribution
V.ccdf=1;                   % use DSSIM
V.refhist.do_discrete=1;   % Assume continious target histogram
V.nsim=10;
V=visim_init(V);
V.Va.it=3;     % Choose Gaussian semivariogram
```

```
V.Va.a_hmax=15; % correlation length (direction of max continuity)
V.Va.a_hmin=15; % correlation length (direction of min continuity)
V=visim(V);

figure(1);visim_plot_sim(V);
print_mul('visim_example_dssim_discrete_1_sim');
figure(2);visim_plot_hist(V);
print_mul('visim_example_dssim_discrete_1_hist');


```

4.2.3 Correlated data errors

Correlated data errors can be specified as an EAS formatted ascii file with the name `datacov_[V.fout]`. If for example the output file for `visim.par` is set to `visim.out`, then the file with correlated data errors should be name `datacov_visim.out`. If this file exist, correlated data errors are read from the file appropriately. If the file does not exist, UNcorrelated data errors are assumed, as given by the fourth column of the `V.fvolsum.fname` file.

4.2.4 Simulation of linear inverse problems

VISIM can be used to solve any linear inverse problem, using both estimation and simulation. The function `G_to_visim` converts a linear inverse problem in Matlab format to a visim format:

```
load lsq_example.mat
V=G_to_visim(x,y,z,d_obs,G,Cd,m0);

% MAKE SURE THE KERNEL LOOKS OK
figure;
subplot(1,2,1);visim_plot_kernel(V); % All kernels
subplot(1,2,2);visim_plot_kernel(V,2); % the 2nd kernel

V.volnh.max=200; % MAX NUMBER OF VOLUMES TO USE
V.Va.a_hmax=0;
V.Va.a_hmin=0;

% Estimation using VISIM
V.nsim=0;
Vest=visim(V);

% Simulation using Matlab
V.nsim=10;
Vsim=visim(V);

% Estimation using Matlab
m0=zeros(V.nx*V.ny,1)+m0;
d0=G*m0;
Cm=V.gvar.*eye(V.nx*V.ny);
m_est = m0 +Cm*G'*inv(G*Cm*G'  + Cd)*(d_obs-d0);
Cm_est = Cm - Cm*G'*inv( G*Cm*G'  + Cd  )*G*Cm;

subplot(2,3,1);
imagesc(V.x,V.y,reshape(m_est,V.ny,V.nx));axis image
cax=caxis;
title_alt('LSQ mean',1)
subplot(2,3,2);
imagesc(V.x,V.y,Vest.etype.mean');axis image;caxis(cax)
title_alt('VISIM LSQ mean',2)
subplot(2,3,3);
```

```
imagesc(V.x,V.y,Vsim.etype.mean');axis image;caxis(cax)
title_alt('VISIM Etype mean',3)

subplot(2,3,4);
imagesc(V.x,V.y,reshape(diag(Cm_est),V.ny,V.nx));axis image
cax=caxis;
title_alt('LSQ var',4)
subplot(2,3,5);
imagesc(V.x,V.y,Vest.etype.var');axis image;caxis(cax)
title_alt('VISIM LSQ var',5)
subplot(2,3,6);
imagesc(V.x,V.y,Vsim.etype.var');axis image;caxis(cax)
title_alt('VISIM LSQ etype',6)
```

4.2.5 Cross borehole tomography example

As VISIM conditions to linear average measurements of the model parameter space, VISIM can be used to draw samples from the a posteriori probability distribution linear inverse problems.

4.2.5.1 Conditional simulation through error simulation

Conditional simulation through error simulation is a fast alternative to traditional conditinal sequential Gaussian simulation, Journel and Huijbregts (1978) page 495. See the following reference for more details: Hansen, T. M. and Mosegaard, K. : VISIM : Sequential simulation for linear inverse problems, Computers and Geosciences 2007, doi:10.016/j.cageo.2007.02.003.

```
V=read_visim('visim_sgsim_cond_3.par');

V.nsim=100;

% Traditional conditional Gaussian simulation
Vseqsim=visim(V);
% Conditional simulation through error simulation
Verrsim=visim_errsim(V);
```

4.2.5.2 Calculating averaging kernels for cross borehole tomography

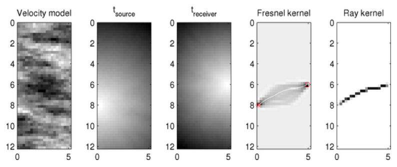
To deal with any kind of linear inverse problem in VISIM the averaging kernel describing the forward problem must be given

The averaging kernel is defined in two text files `visim_volgeom.eas` (defining the geometry of each average kernel) and `visim_volsum.eas`. (giving the observed average and measurement error for each defined volume average.

These two files can be calculated for tomography problems with arbitrary source-receiver geometry, and for a specific velocity model. Both the high frequency approximation to the wave equation, rays, and Fresnel zone based kernels can be generated using the `visim_setup_punch`

```
V=read_visim('sgsim_reference.par');
nx=V.nx;
ny=V.ny;
nz=V.nz;

m_ref=read_eas('visim_sgsim_refmod.eas');
m_ref=reshape(m_ref(:,3),ny,nx)';
% m_ref=zeros(nx,ny)+0.13;

S=linspace(1,11.5,7);
R=linspace(2,10,7);

[ss,rr]=meshgrid(S,R);
```

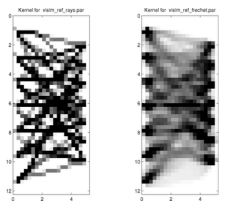
```
S=[ss(:).*0+.1 ss(:)];
R=[rr(:).*0+4.9 rr(:)];

type=1;  % [1]: Ray approximation, [2]: Fresnel zone based kernels
doPlot=1;% [0]: No visual progress, [1]: Plot all kernels as they are computed.

% CALCULATE GEOMETRY IN REF MODEL
[V_ray,G_ray]=visim_setup_punch(V,S,R,m_ref,[],[],'ref_rays',type,doPlot);
type=2;  % [1]: Ray approximation, [2]: Fresnel zone based kernels
[V_fre,G_fre]=visim_setup_punch(V,S,R,m_ref,[],[],'ref_frechet',type,doPlot);
```



See more info at Section 8.2.22

To visualize the generated averaging kernels use for example :

```
subplot(1,2,1)
visim_plot_kernel(V_ray);caxis([0 .1])
subplot(1,2,2)
visim_plot_kernel(V_fre);caxis([0 .1])
```



Now we compute the observed travel time from the refernce model and the current ray geometry

```
t_obs=G_ray*m_ref(:);
t_err=0.*t_obs.*.01;
[V_tomo]=visim_setup_punch(V,S,R,m_ref,t_obs,t_err,'tomo_ray',type,doPlot);
```

This generates the filename `visim_tomo_ray.par`. This parameter file can now be used to perform estimation and/or simulation :

```
V_tomo.cond_sim=3;    % condition to volume averages only (no point data)
V_tomo.nsim=100;      % 100 realizations
V_tomo.volh.max=100; % max 100 average data in the neighborhood.
V_tomo=visim(V_tomo);
```

4.2.5.3 Linear inversion : Cross borehole tomography example

Chapter 5

SNESIM - Single Normal Equation SIMulation

This chapter discuss how to run SNESIM from within Matlab. SNESIM is original Fortran code developed for Single Normal Equation SIMulation method developed by Sebastian Strebelle.

This fortran based implementation has been superceeded by an implementaion is available through S-GeMS. See the chapter [?title].

5.1 Working with SNESIM and mGstat

mGstat implements 4 m-files that allow interactions with SNESIM Here we make no effort to explain the meaning of all the options for the snesim parameter file, but refer to the documenation for SNESIM

5.1.1 Working with SNESIM and mGstat

Get a copy of a snesim parameter file, as well as the associated training image and data templates using “snesim_init”:

```
S = snesim_init;
S =

             fconddata: [1x1 struct]
                  ncat: 2
              cat_code: [0 1]
            pdf_target: [0.7000 0.3000]
         use_vert_prop: 0
             fvertprob: [1x1 struct]
      pdf_target_repro: 1
        pdf_target_par: 0.5000
           debug_level: -2
                fdebug: [1x1 struct]
                   out: [1x1 struct]
                  nsim: 1
                    nx: 80
                   xmn: 0.2500
                  xsiz: 0.5000
                    ny: 120
                   ymn: 0.2500
                  ysiz: 0.5000
                    nz: 1
                   zmn: 0.2500
                  zsiz: 0.5000
                 rseed: 500
             ftemplate: [1x1 struct]
```

```
              max_cond: 16
      max_data_per_oct: 0
       max_data_events: 20
            n_mulgrids: 2
    n_mulgrids_w_stree: 1
                   fti: [1x1 struct]
                  nxtr: 250
                  nytr: 250
                  nztr: 1
                  hmax: 10
                  hmin: 10
                 hvert: 5
                  amax: 7
                  amin: 3
                 avert: 0
               parfile: 'snesim.par'
```

This will read the snesim parameter file into a Matlab structure that can be easily altered.

This SNESIM `S` structure can be written to a SNESIM parameter files using : “write_snesim”:

```
write_snesim(S,'snesim.par');
```

A SNESIM parameter file can be read into a Matlab structure `S`, using: “read_snesim”:

```
S=read_snesim('snesim.par');
```

SNESIM can be from Matlab using: “snesim”:

```
S = snesim_init;
S.nsim = 10;
S = snesim(S);
```

The output from running snesim is located in the data structure as `S.D`. In the present case:

```
size(S.D)
80 120 10
```

Thus to plot the realizations one could use

```
for i=1:S.nsim
  subplot(4,3,i);
  imagesc(S.x,S.y,S.D(:,:,i));
  axis image
end
```

Chapter 6

S-GeMS - The Stanford Geostatistical Modeling Software

This chapter discuss how to run S-GeMS from within Matlab.

6.1 Install S-GeMS

See Section 1.2.4 on details how to install S-GeMS on Windows and Linux.

6.2 S-GeMS data format

S-GeMS handles two data formats: The classical ASCII GEOEAS format, that has been widely used in the geostatistical community. In addition, S-GeMS make use of a new in BINARY format. The binary format is much faster to work with, and handles both point set data and grid data, will full description of the grid properties (cell size, origin, grid size).

In order to run S-GeMS interactively from Matlab only the binary format can be used, as there is no way to instruct S-GeMS about grid size properties reading a EAS file.

Reading and writing of the GEOEAS format are done using the Section 8.1.76 and Section 8.1.104 function.

Binary S-GeMS formatted data (both point set and grid data) can be read using the Section 8.4.13 function.

Binary point set data can be written using the Section 8.4.20 function, and binary grid data can be written using the Section 8.4.19 function, and

6.2.1 GEOEAS to S-GeMS

EAS files can be converted to S-GeMS-binary formatted files using Section 8.4.1.

6.2.1.1 GEOEAS Point Set to S-GeMS-binary

An EAS with data formatted as a point-set, the data section starts with 'ndim' columns defining the location in ndim-space, followed by N columns of DATA.

Use the following syntax:

```
O=eas2sgems(file_eas,file_sgems,ndim);
```

Convert a 3D EAS file with two data sets (5 cols, 3 dimensions) using

```
ndim=3
eas2sgems('file.eas','file.sgems',ndim)
```

Convert a 2D EAS file with two data sets (4 cols, 2 dimensions) using

```
ndim=2
eas2sgems('file.eas','file.sgems',ndim)
```

6.2.1.2 GEOEAS GRID to S-GeMS-binary

For an EAS with data formatted as GRIDS, the data section consist of N colums, representing N grids. An EAS not does not contain information about the cell size (dx,dy,dx) cell size, or the location of the first cell for each dimension (x0,y0,z0).

It 'may' (not part of strict format) contain information about the size of the grid(s) in the first line 'xxxxx (90x10x1)'.

Use the following syntax:

```
O=eas2sgems(file_eas,file_sgems,nx,ny,nz,dx,dy,dz,x0,y0,z0);
```

Convert an EAS file with 2 grids, assuming the grid size is given in the EAS header ('HEADER (60x70x1)'), and(dx,dy,dz)=(1,1,1), (x0,y0,z0)=(0,0,0):

```
ndim=2
eas2sgems('file.eas','file.sgems')
```

Same as above, but all manual settings:

```
eas2sgems('file.eas','file.sgems',60,70,1,1,1,1,0,0,0);
```

Same as above, but but (x0,y0,z0)=(10,10,6):

```
eas2sgems('file.eas','file.sgems',60,70,1,10,10,6,0,0,0);
```

6.2.2 S-GeMS to EAS

S-GeMS-binary formatted files can be converted to EAS ASCII formatted files using Section 8.4.3. Simply call :

```
sgems2eas('file.sgems','file.eas');
```

6.3 Using S-GeMS

In order to make full use of the Matlab interface to S-GeMS some knowledge of the use of S-GeMS is essential. The book Applied Geostatistics with SGeMS (Remy, Boucher and Wu, Cambridge University Press, 2009), written by the developers of S-GeMS is highly recommended.

The Matlab interface to S-GeMS relies on a feature of S-GeMS that allow S-GeMS to read and execute a series of Python commands from the command line, without the need to load the graphical user interface, as for example:

```
sgems -s sgems_python_script.py
```

The Matlab interface consists of methods and functions to automatically create such a Python script, execute the script using S-GeMS and load the simulated/estimated results into Matlab

One function (Section 8.4.7) handles these actions allowing simulation on grids in the following manner:

1. Define a parameter file (Section 8.4.6, Section 8.4.15)

2. Write a python script that (Section 8.4.8)
   (a) sets up a grid or pointset where simulation or estimation is performed
   (b) performs the simulation/estimation
   (c) export the simulated/estimated data
3. Load the data into Matlab (Section 8.4.18)

For a complete list of S-GeMS related commands on mGstat see Section 8.4

6.3.1 Sequential simulation using S-GeMS

This section contains a rather detailed explanation of using S-GeMS to perform simulation. Much more compact example can be found in the following chapters.

Unconditional and conditional sequential simulation can be performed using Section 8.4.7 :

```
S = sgems_grid(S);
```

Where `S` is a Matlab data structure containing all the information needed to setup and run S-GeMS

A number of different simulation algorithms are available in S-GeMS The behavior of each algorithm is controlled through an XML file. Such an XML file can for example be exported from S-GeMS by choosing to save a parameter file for a specific algorithm.

Such an XML formatted parameter is needed to perform any kind of simulation. A number of 'default' parameter files available using the Section 8.4.6 function. For example to obtain a default parameter file for sequential Gaussian simulation use

```
S = sgems_get_par('sgsim')

S =

    xml_file: 'sgsim.par'
         XML: [1x1 struct]
```

As can be seen the adds the name of the XML file (S.xml_file) as well as a XML data structure in the S-GeMS matlab structure `S.XML`.

All supported simulation/estimation types can be found calling `sgems_get_par` without arguments:

```
>> sgems_get_par
sgems_get_par : available SGeMS type dssim
sgems_get_par : available SGeMS type filtersim_cate
sgems_get_par : available SGeMS type filtersim_cont
sgems_get_par : available SGeMS type lusim
sgems_get_par : available SGeMS type sgsim
sgems_get_par : available SGeMS type snesim_std
```

Now all parameters for 'sgsim' simulation can be set directly from the Matlab command line. To see the number of fields in the XML file (refer to the S-GeMS book described above for the meaning of all parameters):

```
>> S.XML.parameters

ans =

                algorithm: [1x1 struct]
                Grid_Name: [1x1 struct]
            Property_Name: [1x1 struct]
          Nb_Realizations: [1x1 struct]
                     Seed: [1x1 struct]
            Kriging_Type: [1x1 struct]
                   Trend: [1x1 struct]
     Local_Mean_Property: [1x1 struct]
        Assign_Hard_Data: [1x1 struct]
               Hard_Data: [1x1 struct]
   Max_Conditioning_Data: [1x1 struct]
        Search_Ellipsoid: [1x1 struct]
    Use_Target_Histogram: [1x1 struct]
             nonParamCdf: [1x1 struct]
               Variogram: [1x1 struct]
```

To see the number of realization :

```
>> S.XML.parameters.Nb_Realizations

ans =

    value: 10
```

To set the number of realization to 20 do:

```
>> S.XML.parameters.Nb_Realizations.value=20;
```

One also need to define the grid used for simulation. This is done through the `S.dim` data structure:

```
%grid size
S.dim.nx=70;
S.dim.ny=60;
S.dim.nz=1;
% grid cell size
S.dim.dx=1;
S.dim.dy=1;
S.dim.dz=1;
% grid origin
S.dim.x0=0;
S.dim.y0=0;
S.dim.z0=0;
```

All the values listed above for the `S.dim` data structure are default, thus if they are not set, they are assumed as listed.

Unconditional simulation is now performed using:

```
>> S=sgems_grid(S);
sgems_grid : Trying to run SGeMS using sgsim.py, output to SGSIM.out
'import site' failed; use -v for traceback
Executing script...

working on realization 1
|#                   |    5%working on realization 2
|##                  |   10%working on realization 3
|###                 |   15%working on realization 4
|####                |   20%working on realization 5
|#####               |   25%working on realization 6
|######              |   30%working on realization 7
|#######             |   35%working on realization 8
|########            |   40%working on realization 9
|#########           |   45%working on realization 10
|##########          |   50%working on realization 11
|###########         |   55%working on realization 12
|############        |   60%working on realization 13
|#############       |   65%working on realization 14
|##############      |   70%working on realization 15
```

```
|###############     |    75%working on realization 16
|################    |    80%working on realization 17
|#################   |    85%working on realization 18
|##################  |    90%working on realization 19
|################### |    95%working on realization 20
|####################|    100%
sgems_read : Reading GRID data from SGSIM.sgems
sgems_grid : SGeMS ran successfully

S =

    xml_file: 'sgsim.par'
         XML: [1x1 struct]
         dim: [1x1 struct]
        data: [4200x20 double]
           O: [1x1 struct]
           x: [1x70 double]
           y: [1x60 double]
           z: 1
           D: [4-D double]
```

As seen above the following field have been added to the S-GeMS matlab structure: `S.x`, `S.y`, `S.z`, `S.data` and `S.D`.

`S.x`, `S.y`, `S.z` are 3 arrays defining the grid.

`S.data`, is the simulated data as exported from S-GeMS. Note the each realization is returned as a list of size nx*ny*nz.

`S.D`, is but a rearrangement of `S.data` into a 4D dimensional data structure, of size (nx,ny,nz,nsim). To visualize for example the 3rd realization use for example:

```
imagesc(S.x,S.y,S.D(:,:,1,3));
```

Conditional simulation can be performed by setting the `S.d_obs` parameter. For example:

```
S.d_obs=[18 13 0 0; 5 5 0 1; 2 28 0 1];
S=sgems_grid(S);
imagesc(S.x,S.y,S.D(:,:,1,3));
```

6.3.1.1 Specification of variogram model

Using sequential Gaussian simulation the semivariogram model is specified in `S.XML.parameters.Variogram`:

```
>> S.XML.parameters.Variogram
ans=
      nugget: 1.0000e-003
   structures_count: 1
         structure_1: [1x1 struct
```

To run 10 simulations with increasing range do for example:

```
for i=1:1:10
  r=i*10;
  S.XML.parameters.Variogram.structure_1.ranges.max=[r];
  S.XML.parameters.Variogram.structure_1.ranges.medium=[r];
  S.XML.parameters.Variogram.structure_1.ranges.min=[r];
  S=sgems_grid(S);
  subplot(4,3,i);imagesc(S.x,S.y,S.D(:,:,1)');
end
```

The variogram model can also be specified using a shorter notation (same format as when using GSTAT):

```
    S.XML.parameters.Variogram=sgems_variogram_xml('0.1 Nug(0) + 0.4 Exp(10) + 0.5 Sph ↩
        (40,30,0.2)');
```

6.3.2 Unconditional sequential Gaussian simulation using S-GeMS

A simple example of unconditional sequential simulation.

```
S=sgems_get_par('sgsim');
S.XML.parameters.Nb_Realizations.value=12;
S=sgems_grid(S);
for i=1:S.XML.parameters.Nb_Realizations.value;
  subplot(4,3,i);
  imagesc(S.x,S.y,S.D(:,:,1,i));
end
```

6.3.3 Conditional sequential Gaussian simulation

Conditioning data can be specified either as a data variable or as an sgems-binary formatted file (see Section 6.2).

6.3.3.1 conditional data as a variable

A simple example of conditional sequential simulation (`examples/sgems_examples/sgems_example_sgsim_conditiona` `m`):

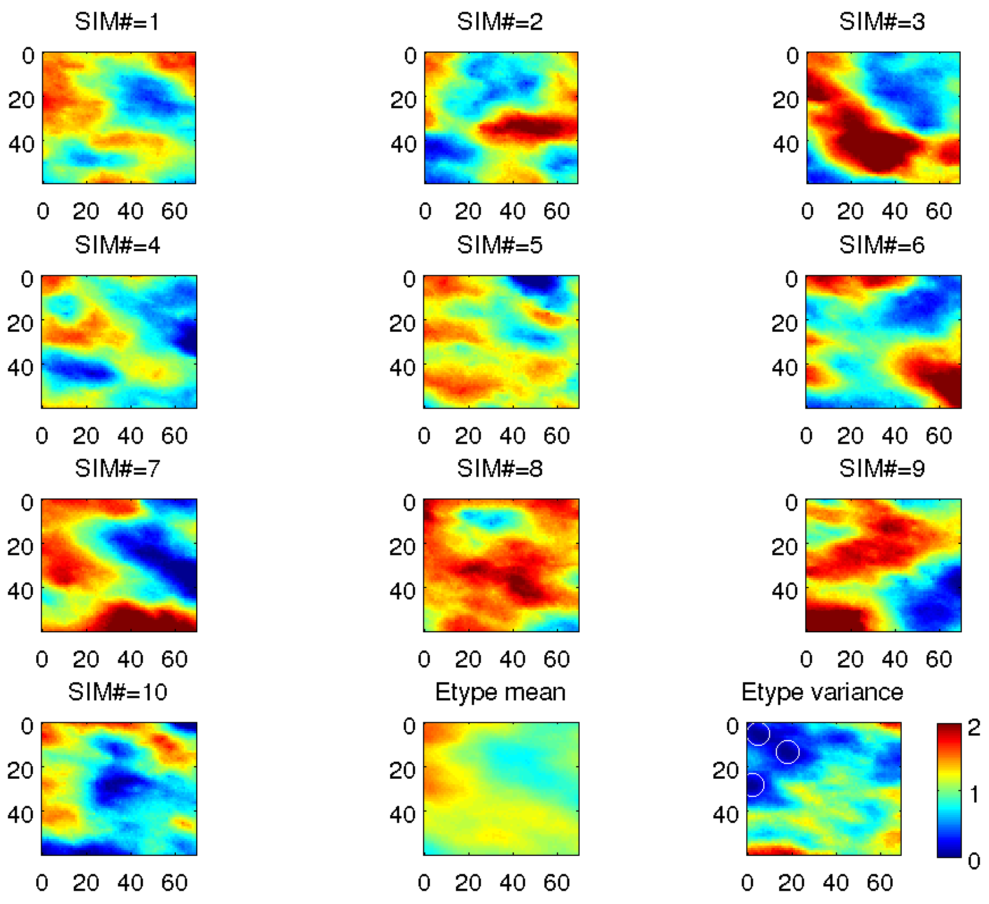
```
% sgems_sgsim_conditional :
%     Conditional SGSIM using hard data from variable

% GET Default par file
S=sgems_get_par('sgsim');

% Define observed data=
S.d_obs=[18 13 0 0; 5 5 0 1; 2 28 0 1];

S.XML.parameters.Nb_Realizations.value=10;
S=sgems_grid(S);

% PLOT DATA
cax=[-2 2];
for i=1:S.XML.parameters.Nb_Realizations.value;
  subplot(4,3,i);
  imagesc(S.x,S.y,S.D(:,:,1,i)');axis image;caxis(cax);title(sprintf('SIM#=%d',i))
end

print('-dpng','sgems_sgsim_conditional')
```

6.3.3.2 conditional data from file

A simple example of conditional sequential simulation (`examples/sgems_examples/sgems_example_sgsim_conditiona` `hard_data_from_file.m`):

```
% sgems_sgsim_conditional_hard_data_from_file :
%     Conditional SGSIM using hard data from file

% GET Default par file
S=sgems_get_par('sgsim');

% Define observed data=
d_obs=[18 13 0 0; 5 5 0 1; 2 28 0 1];
sgems_write_pointset('obs.sgems',d_obs);
S.f_obs='obs.sgems';

```

```
S.XML.parameters.Nb_Realizations.value=10;
S=sgems_grid(S);


%% PLOT DATA
cax=[-2 2];
for i=1:S.XML.parameters.Nb_Realizations.value;
  subplot(4,3,i);
  imagesc(S.x,S.y,S.D(:,:,1,i)');axis image;caxis(cax);title(sprintf('SIM#=%d',i))
end
[m,v]=etype(S.D);
subplot(4,3,11);
imagesc(S.x,S.y,m');axis image;caxis(cax);title('Etype mean')
subplot(4,3,12);
imagesc(S.x,S.y,v');axis image;caxis([0 2]);title('Etype variance')
hold on
plot(d_obs(:,1),d_obs(:,2),'wo','MarkerSize',10)
hold off
colorbar

print('-dpng','sgems_sgsim_conditional_hard_data_from_file')

```



Sequential Gaussian conditional simulation

6.3.4 Unconditional SNESIM and FILTERSIM Gaussian simulation using S-GeMS

A simple example of unconditional SNESIM AND FILTERSIM simulation.

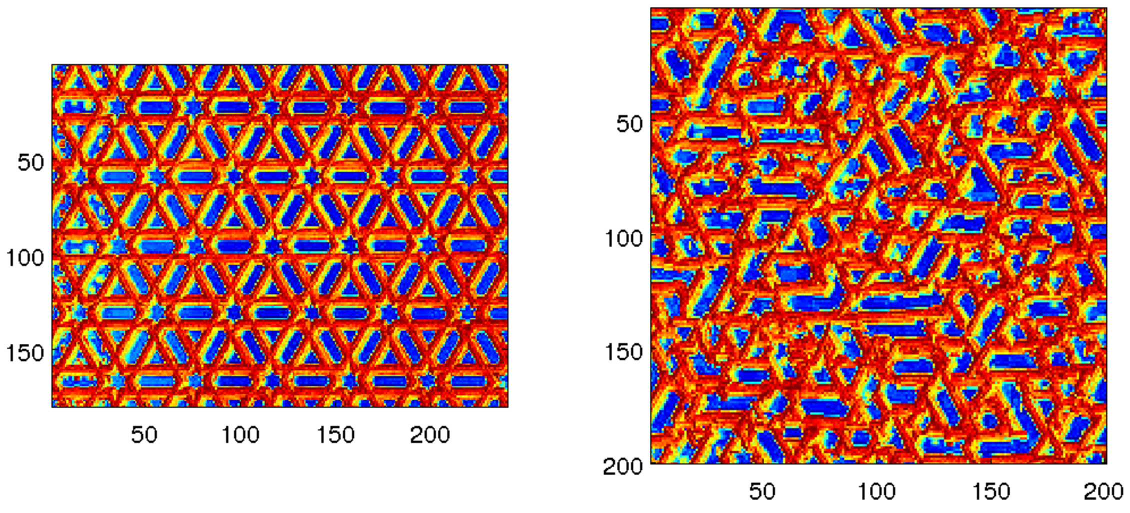
```
S1=sgems_get_par('snesim_std'); %
% Note that S1.ti_file is automatically set.
% simply change this to point to another training to use.
S1.XML.parameters.Nb_Realizations.value=4;

S2=sgems_get_par('filtersim_cont');
S2.XML.parameters.Nb_Realizations.value=4;

S1=sgems_grid(S1);
S2=sgems_grid(S2);


for i=1:S1.XML.parameters.Nb_Realizations.value;
  subplot(S1.XML.parameters.Nb_Realizations.value,2,i);
  imagesc(S1.x,S1.y,S1.D(:,:,1,i));axis image;

  subplot(S1.XML.parameters.Nb_Realizations.value,2,i+S1.XML.parameters.Nb_Realizations. ↩
      value);
  imagesc(S2.x,S2.y,S2.D(:,:,1,i));axis image;
end
```

6.3.5 Convert image to training image;

Using a JPG file from FLICKR as training image:

```
% sgems_example_to_from_image : convert image and use as training image

% LOAD IMAGE AND CONVERT TO SGeMS binary TRAINING IMAGE
%file_img='1609350318_7300f07360_m_d.jpg'; % larger pattern
file_img='1609350318_7300f07360_m_d.jpg'; % smaller pattern
f_out=sgems_image2ti(file_img);
TI=sgems_read(f_out);


% SETUP FILTERSIM
S=sgems_get_par('filtersim_cont');
S.ti_file=f_out;
S.XML.parameters.PropertySelector_Training.grid=TI.grid_name;
S.XML.parameters.PropertySelector_Training.property=TI.property{1};
S.XML.parameters.Nb_Realizations.value=1;


S.dim.x=[1:1:200];
S.dim.y=[1:1:200];
S.dim.z=[0];

% RUN SIMULATION
S=sgems_grid(S);


% VISUALIZE RELIZATION
subplot(1,2,1);
imagesc(TI.x,TI.y,TI.D(:,:,:,1)');axis image;
subplot(1,2,2);
imagesc(S.x,S.y,S.D(:,:,:,1)');axis image;
```

```

print('-dpng','sgems_example_ti_from_image');
```



Example of converting an image and using it for continuous filtersim simulation

6.3.6 Simulation demonstration

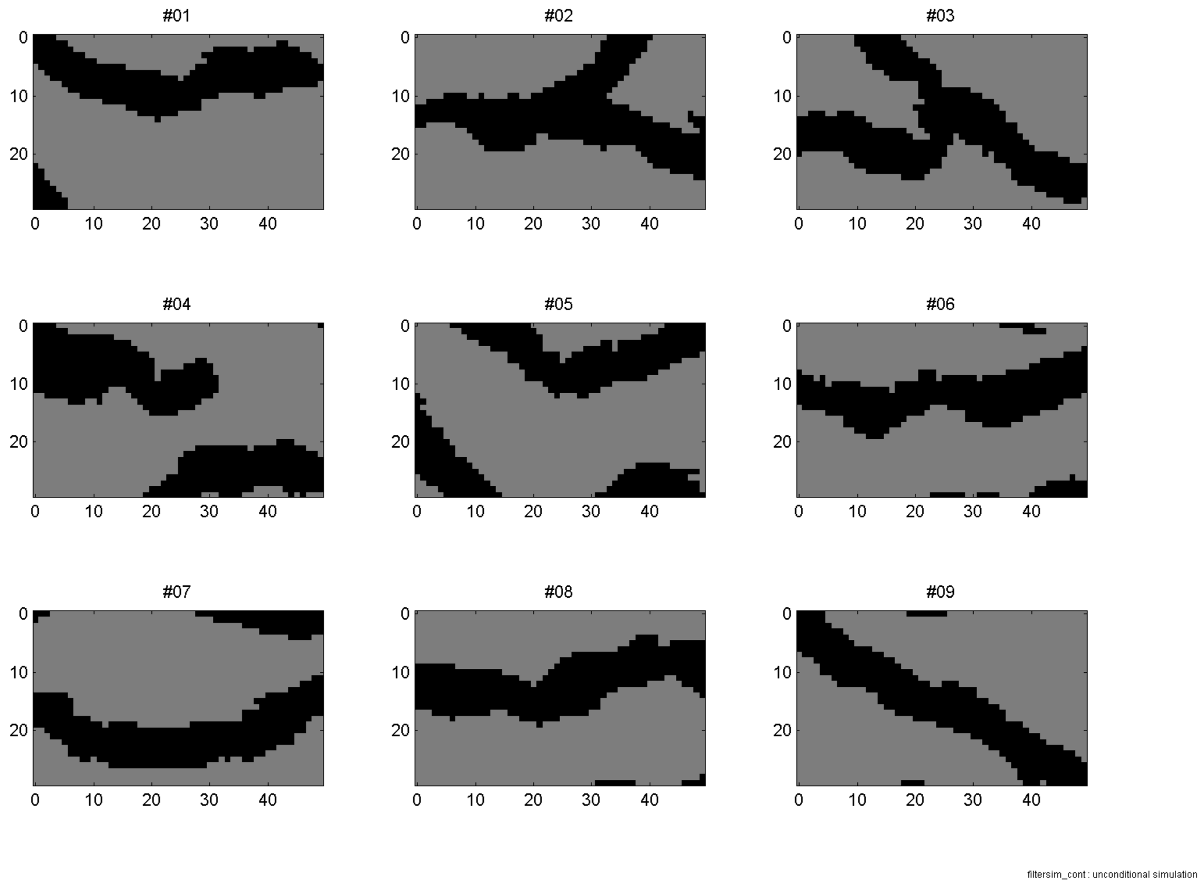
Demonstration simulation of mGstat supported simulation algorithms can be performed using Section 8.4.5. To see a list of supported simulation algorithms use:

```
>> sgems_get_par
sgems_get_par : available SGeMS type dssim
sgems_get_par : available SGeMS type filtersim_cate
sgems_get_par : available SGeMS type filtersim_cont
sgems_get_par : available SGeMS type lusim
sgems_get_par : available SGeMS type sgsim
sgems_get_par : available SGeMS type snesim_std
```

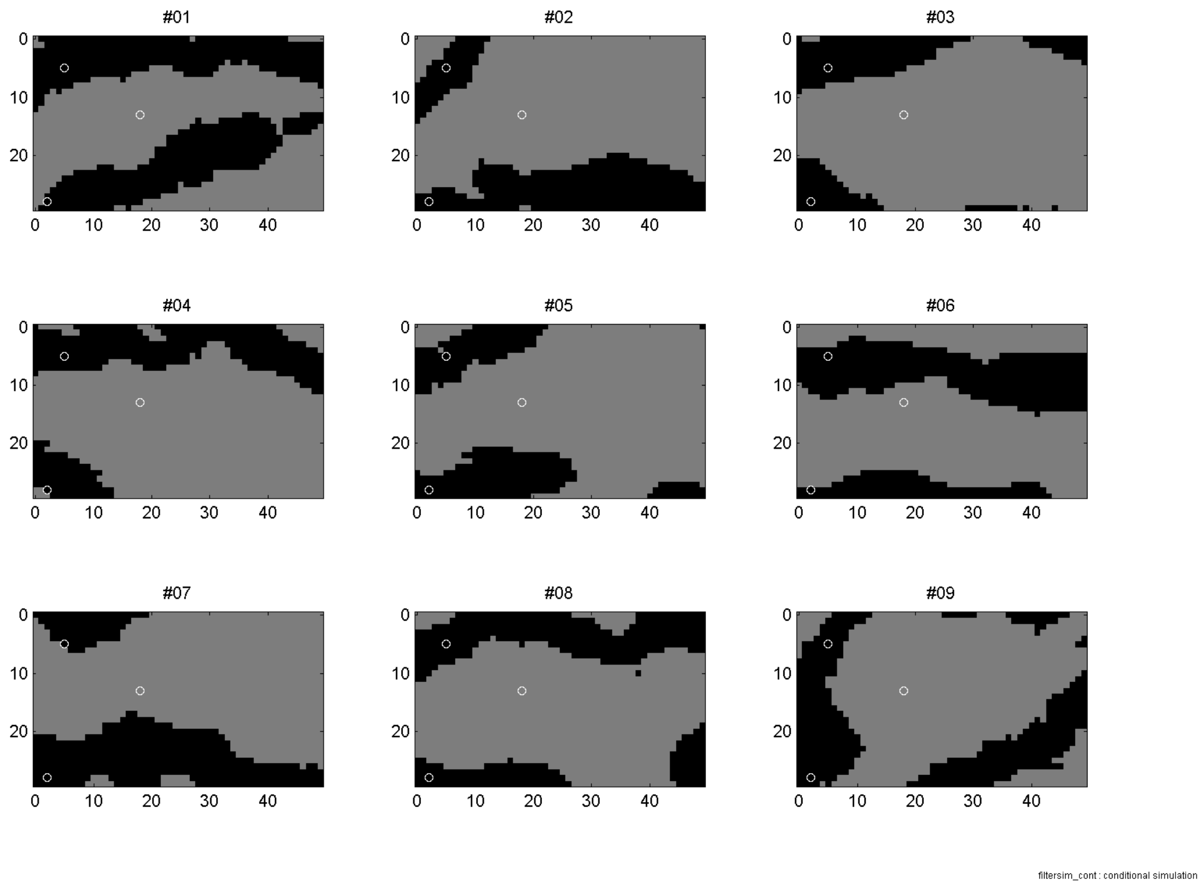
To run a demonstration of continuous filtersim simulation using the 'filtersim_cont' algorithm do

```
>> sgems_demo('filtersim_cont');
```

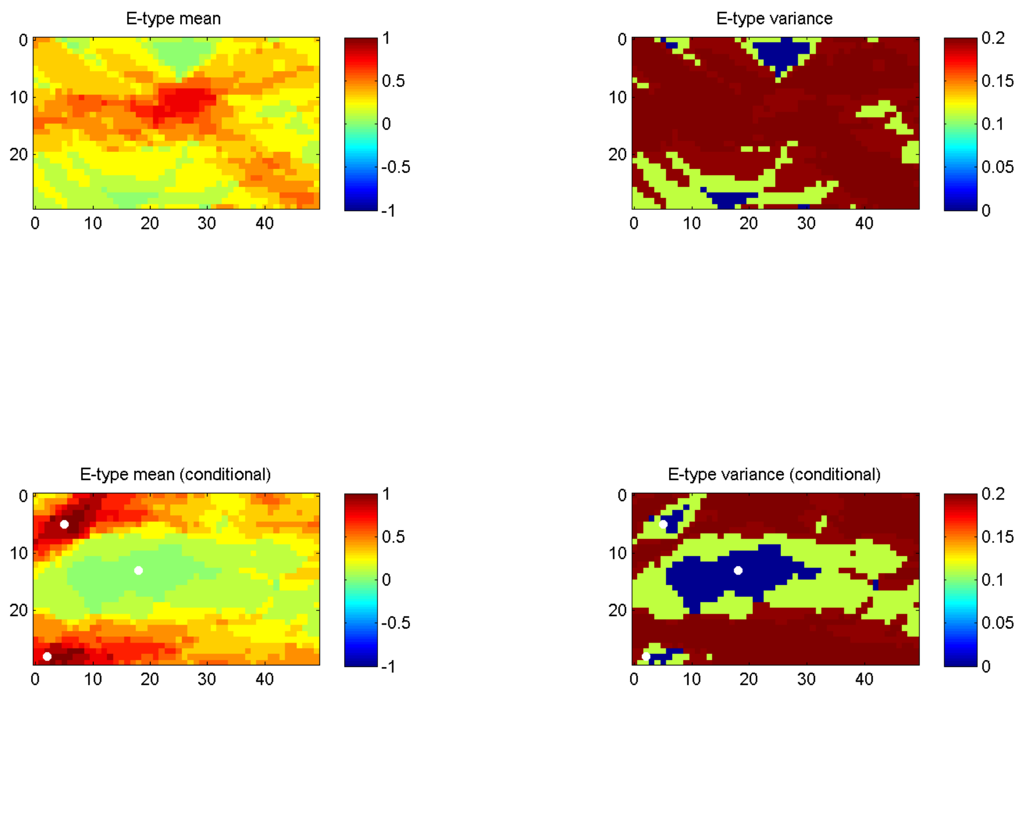
This will perform both unconditional and conditional simulation, and visualize the results as for example here below.



Unconditional simulation



Conditional simulation



E-type on conditional simulations

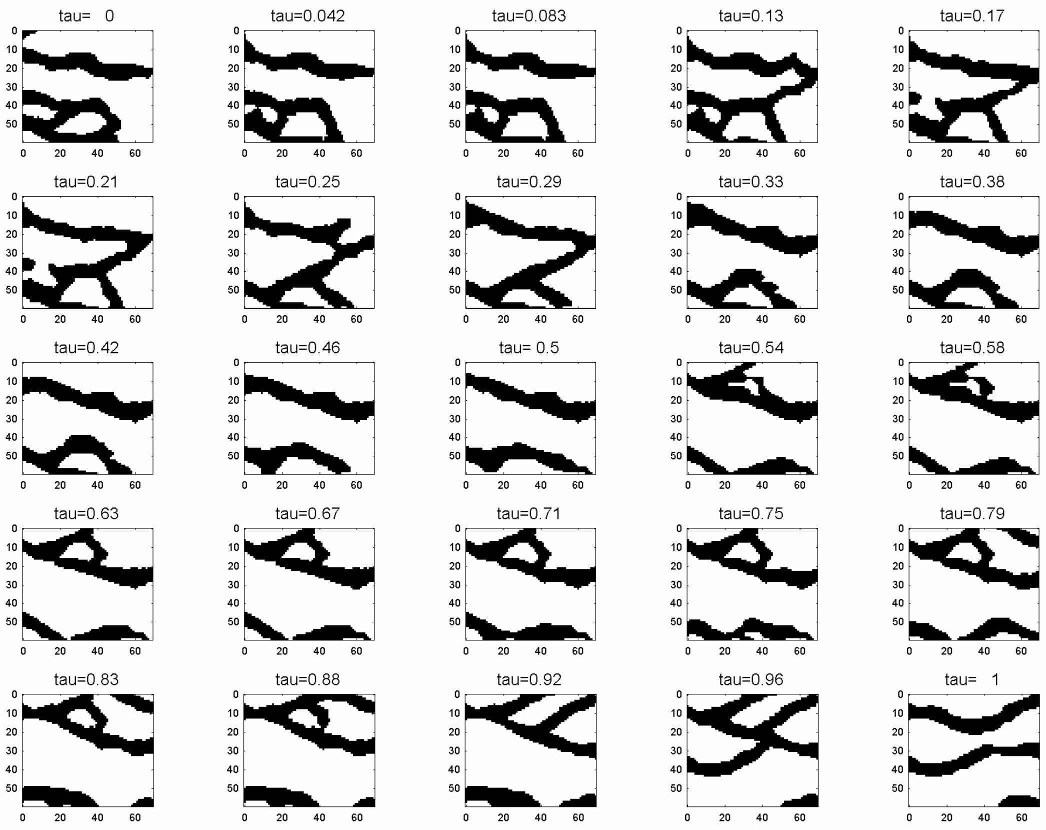
Running Section 8.4.5 without arguments will run the demonstration using all supported simulation algorithms.

6.3.7 Probability perturbation (PPM)

`examples/sgems-examples/sgems_example_ppm.m` is an example of applying the probability perturbation method, where one realization can be gradually deformed into another independent realization.

```
% sgems_example_ppm : example of using PPM
%

% get default snesim parameter file
S=sgems_get_par('snesim_std');
%S=sgems_get_par('filtersim_cate'); % SOFT PROB NOT YET IMPLEMENTED FOR
%FILTERSIM

% generate starting realization
S.XML.parameters.Nb_Realizations.value=1;
S=sgems_grid(S);

% loop over array of TAU values
r_arr=linspace(0,1,25);
Sppm{1}=S;
for i=2:length(r_arr)
    % perform PPM with tau=r_arr(i)
    Sppm{i}=sgems_ppm(S,S.O,r_arr(i));
```

```
end

% Visualize results
figure;set_paper('landscape');
title('TI')
for i=1:length(r_arr)
    ax(i)=subplot(5,5,i);
    imagesc(S.x,S.y,Sppm{i}.D');axis image;
    set(gca,'FontSize',6)
    title(sprintf('tau=%4.2g',r_arr(i)),'FontSize',10)
end
colormap(1-gray)
print('-dpng','-r200','sgems_example_ppm.png');

```



Example of applying the Probability Perturbation Method using S-GeMS

Chapter 7

Misc

.

7.1 Traveltime calculation using FAST

Colin Zelts FAST code contains a program (nfd) to compute first arrival times in a square grid by solving the eikonal equation. An m-file wrapper is available in mGstat to easily call `nfd`

7.1.1 Compile nfd using g77

To use nfd form the FAST package the nfd binary must be copied to `[MGSTAT_ROOT]/bin/nfd`.

Compiling of the FAST codes is non trivial on the Linux platforms tested, using the Makefiles released as part of FAST. The help for compiling fast found here below, was tested on Linux (Redhat and Ubuntu) using goth F77 and the Intel Fortran Compiler (ifort) Download fast.tar.gz and compile 'nfd' using

```
wget http://terra.rice.edu/department/faculty/zelt/fast.tar.gz
tar xvfz fast.tar.gz
cd fast
find ./pltlib -name '*.f' -exec g77 -c {} \;
find ./fd -name '*.f' -exec g77 -c {} \;
g77 -o nfd main.o model.o time.o findiff.o findiff2d.o stencils.o stencils2d.o misc.o plt.o ↩
     blkdat.o nopltlib.o
cp nfd [MGSTAT_ROOT]/bin/.
```

In addition you may need to change `fd/fd.par` to enabale models larger than nx*ny*nz = 601*100*25. Use for example

```
     parameter(nxmax=601, nymax=100, nzmax=225, ncolour=10,
     +           nsources=99)
```

Then you should be ready to use nfd.

To get rid of the message :FD: finite difference traveltime calculation, during each run of 'nfd' you can comment out lines 92-93 in `fd/main.f`, such that

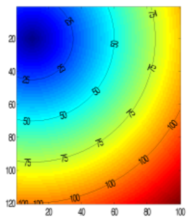
```
      write(6,335)
335   format(/'FD: finite difference traveltime calculation')
```

is changed to

```
c      write(6,335)
c335   format(/'FD: finite difference traveltime calculation')
```

7.1.2 fast_fd_2d

```
nx=100;ny=120;
x=[1:1:nx];
y=[1:1:ny];
v=ones(ny,nx);
S=[10 20];
t = fast_fd_2d(x,y,v,S);
imagesc(x,y,t);axis image
hold on
[cs,h]=contour(x,y,t,[25:25:100],'k-');
clabel(cs,h,'labelspacing',100)
hold off
```



7.1.3 fast_fd_2d_traveltime

fast_fd_2d_traveltime computes the traveltime between a set of Sources (`Sources`) and Receivers (`Receivers`)

Note that the size of Sources and Recivers MUST be the same. If you are ineterested in calculating the traveltime between all rays between a set of Sources and receivers consider using Section 8.5.6

```
nx=100;ny=120;
x=[1:1:nx];
y=[1:1:ny];
v=ones(ny,nx);
Sources  =[2 10 ; 2 80];
Receivers=[10 10;100 80];
t=fast_fd_2d_traveltime(x,y,v,Sources,Receivers)
plot(t);
xlabel('raynumber');ylabel('travel time')
```

7.1.4 fast_fd_2d_traveltime_matrix

fast_fd_2d_traveltime_matrix computes the traveltime from a number of sources (`Sources`) to a number of Receivers (`Rece-ivers`)

```
nx=100;ny=120;
x=[1:1:nx];
y=[1:1:ny];
v=ones(ny,nx);
Sources=[2 10;2 80];
nr=40;
Receivers=[ones(nr,1)*nx-2,linspace(2,ny-1,nr)']
t=fast_fd_2d_traveltime_matrix(x,y,v,Sources,Receivers)
plot(t);
xlabel('raynumber');ylabel('travel time')
```

7.1.5 fast_fd_clean

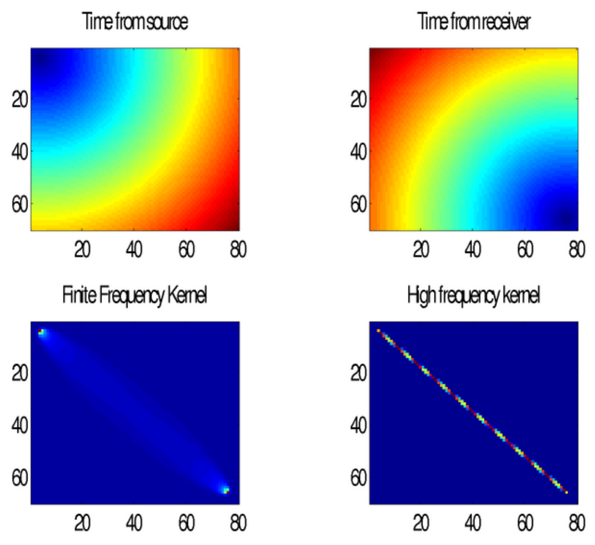
`fast_fd_2d_clean` deletes a large number of files from disk, generated running fast_fd_2d.

7.1.6 Computing sensitivity kernels using nfd

7.1.6.1 Finite and High frequency approximation kernel

To calculate finite frequency and high frequency sensitivity kernel of one set og source and receivers use :

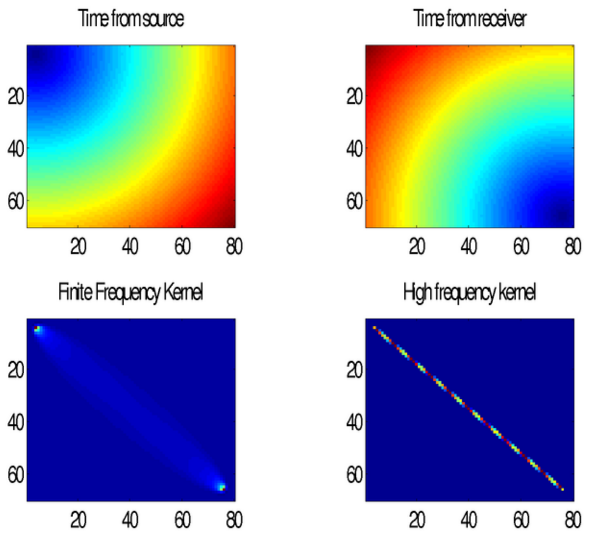
```
nx=80;ny=70;
x=[1:1:nx];
y=[1:1:ny];
z=1;
v=ones(ny,nx);  % Velocity field
S=[4 4];        % Sources
R=[nx-4 ny-4];  % Receiver

T=8;            % Dominant period
alpha=1;        %

[K,RAY,timeS,timeR,raypath,raylength]=kernel(v,x,y,z,S,R,T,alpha);
subplot(2,2,1);imagesc(x,y,timeS);title('Time from source');axis image
subplot(2,2,2);imagesc(x,y,timeR);title('Time from receiver');axis image
subplot(2,2,3);imagesc(x,y,K);title('Finite Frequency Kernel');axis image
subplot(2,2,4);imagesc(x,y,RAY);title('High frequency kernel');axis image
```



To calculate finite frequency and high frequency sensitivity kernel of more than one set og source and receivers `kernel_multiple` should be used, as this is more eficient than calling `kernel` many times:

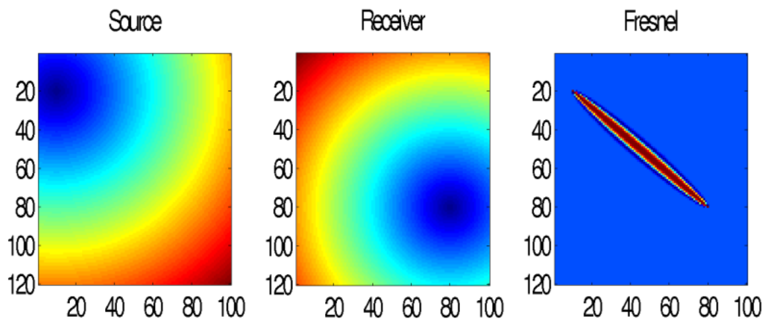
```
nx=80;ny=70;
x=[1:1:nx];
y=[1:1:ny];
z=1;
v=ones(ny,nx);  % Velocity field
S=[4 4 ; 4 10 ;4 ny-4];        % Sources
R=[nx-4 ny-4;nx-4 ny-4;nx-4 ny-4];  % Receiver

T=8;            % Dominant period
alpha=1;        %
```

```
[K,RAY,Gk,Gray,timeS,timeR,raypath,raylength]=kernel_multiple(v,x,y,z,S,R,T,alpha);
subplot(1,2,1);imagesc(x,y,reshape(sum(Gk),ny,nx));title('3 finite frequency kernels'); ↩
    caxis([0 1]);axis image
subplot(1,2,2);imagesc(x,y,reshape(sum(Gray),ny,nx));title('3 high frequency kernels');axis ↩
     image
```



7.1.6.2 Finite frequency kernel

```
nx=40;ny=70;
x=[1:1:nx];
y=[1:1:ny];
v=ones(ny,nx);
SR=[4 4 ;nx-4 ny-4];
t = fast_fd_2d(x,y,v,SR);

dt=t(:,:,1)+t(:,:,2);
dt=dt-min(dt(:));
F = munk_fresnel_2d(1,dt);
subplot(1,3,1);imagesc(x,y,t(:,:,1));axis image;title('Source')
subplot(1,3,2);imagesc(x,y,t(:,:,2));axis image;title('Receiver')
subplot(1,3,3);imagesc(x,y,F);axis image;title('Fresnel')
```



Chapter 8

Matlab Reference

bla

8.1 Core functions

8.1.1 Contents

```
mGstat Toolbox
Version 0.1 Feb 18, 2004

mGstat COMMANDS
  mgstat_verbose - display verbose information
  krig - simple/ordinary/tren kriging
  precal_covar - precalculate covariance matrix
  semivar_synth
  semivar_exp
  nscore : Normal socre transformation
  inscore : Normal socre back transformation

  sgsim    : Sequential Gaussian Simulation
  dssim    : Direct sequential simulation
  dssim-hr : Direct sequential simulation with histogram reprod.
  etype : E-Type from reaslizations.

GSTAT SPECIFIC COMMANDS
  gstat         - call gstat with parfile of mat-structure
  gstat_convert - convert binary GSTAT output to ASCII
  gstat_krig    - Point kriging
  --gstat_cokrig  - Point cokriging
  --gstat_krig2d  - 2D kriging
  --gstat_cokrig2d- 2D cokriging
  gstat_binary  - returns the path to the binary gstat
  gstat_demo    - mGstat demos
  semivar_exp_gstat -

IO
  read_petrel    - read petrel ascii formatted file
  read_gstat_par    - read gstat parameter file
  write_gstat_par   - write gstat parameter file
  read_eas          - read EAS ascii formatted files
  write_eas         - write EAS ascii formatted files
  read_arcinfo_ascii  - read ARCINFO ascii formatted files
  write_arcinfo_ascii - write ARCINFO ascii formatted files

MISC
  nanmean - mean of array, where NaN are excluded.
  strip_space.m
  format_variogram.m
  deformat_variogram.m
  vonk2d  - random field generator
  watermark - adds label to figure
  progress_txt - ascii progress bar


  Overloaded methods:
     serial/Contents
     mmreader/Contents
     audiorecorder/Contents
     audioplayer/Contents
     VideoReader/Contents
     instrument/Contents
     rsmd/Contents
     resultset/Contents
     drivermanager/Contents
     driver/Contents
     dmd/Contents
     dbtbx/Contents
     database/Contents
     cursor/Contents
```

8.1.2 CreateMisfitFunction

```
CreateMisfitFunction : Dynamically created function to be used for
                       semivariogram optimization
```

8.1.3 MakeXmlRef

8.1.4 arcinfo2eas

```
arcinfo2eas : convert ArcInfo file to EAS

CALL
   arcinfo2eas(file_arcinfo,file_eas);

or
   arcinfo2eas(file_arcinfo);
   using the same file name as the arcinfo file
   but with the 'eas' file extension.
```

8.1.5 block_log

```
block_log : block a log

Call:
  [mz,z_out]=block_log(val,z,bz);
```

8.1.6 cokrig_sk

```
cokrig_sk : Simple CoKriging

Call :
 function [d_est,d_var,lambda_sk,K_sk,k_sk]=cokrig_sk(pos_known,val_known,pos_est,V,val_0 ↩
     );

TMH/2005
```

8.1.7 colorbar_shift

```
colorbar_shift : Adds a colorbar to the current figure, with no reshaping

Before printing to a PS file you may need to set :
set(gca,'ActivePositionProperty','Position')


example :
subplot(2,2,1)
imagesc(peaks)
subplot(2,2,2)
imagesc(peaks)
set(gca,'ActivePositionProperty','Position')
colorbar_shift;
```

8.1.8 colormap_nan

```
colormap_nan

Replaces all NaN values with a specific color, and rescales the
colorbar appropriately;


example :
d=peaks(200);
d(find(d<0))=NaN;
figure(1);imagesc(d);
colormap(hot);
colormap_nan;
drawnow;
pause(2)


figure(2);imagesc(d);
colormap_nan(jet,[.2 .9 .1]);
colorbar;drawnow;
```

```
pause(2);

figure(3);imagesc(d);
colormap_nan(jet(1000),[.2 .9 .1]);
colorbar
```

8.1.9 colormap_squeeze

```
colormap_squeeze

Call :
  colormap_squeeze(dperc);
  dperc=[0 .. 0.5];

  imagesc(peaks);
  colormap_squeeze(.1);
  pause(1);
  colormap_squeeze(.1);
```

8.1.10 comb_cprob

```
comb_cprob : PDF combination using permancne of ratios

Call :
 pAgBC=comb_cprob(pA,pAgB,pAgC)


pA    : Prob(A)
pAgB  : Prob(A|B)
pAgC  : Prob(A|C)
pAgBC : Prob(A|B,C)

Combination of conditional probabilities
based on permanence of updating ratios.

Journel, An Alternative to Traditional Data Independence
Hypotheses, Math Geol(34), 2002
```

8.1.11 comb_cprob_ind

```
comb_cprob_ind : Combination of two independent conditional PDF

Call :
   pAgBC=comb_cprob_ind(pA,pAgB,pAgC)

pA    : Prob(A)
pAgB  : Prob(A|B)
pAgC  : Prob(A|C)
pAgBC : Prob(A|B,C)
```

```
TMH/2005
```

8.1.12 comb_cprob_nd

```
comb_cprob_nd : PDF combination using permancne of ratios

Combination of 'nd' conditional probabilities
based on permanence of updating ratios.

Call :
 pAgND=comb_cprob(pA,pAgND,wAgND)


pA    [scalar] : Prob(A)
pAgND [array]  : Prob(A|N1),Prob(A|N2),...,Prob(A|ND)
wAgBC [array]  : Weight of each cprob
pAgBC [scala]  : Prob(A|ND)

Combination of conditional probabilities
based on permanence of updating ratios.

Journel, An Alternative to Traditional Data Independence
Hypotheses, Math Geol(34), 2002
```

8.1.13 covar_exp

```
 semivar_exp : Calcualte experimental variogram

[hc,garr,h,gamma,hangc,head,tail]=semivar_exp(pos,val,nbin,nbinang)

 pos : [ndata,ndims]
 val : [ndata,ndata_types]

 nbin : [integer] number of bins on distance anxes
        [array] if specified as an array, this is used.

 nbinang : [integer] number of arrays between 0/180 degrees
                     (default 1)
 Example isotrop:
   [hc,garr]=semivar_exp(pos,val);
   plot(garr,hc);

 Example directional [0,45,90,135,180]:
   [hc,garr,h,gamma,hangc]=semivar_exp(pos,val,20,4);
   plot(garr,hc);
   legend(num2str(hangc'))


 TMH/2005
```

8.1.14 cpdf

```
cpdf : cumulative probability density function

[pk_obs]=cpdf(alldata,d_obs,doPlot)

finds pk quantiles for data (d_obs),
based on a series of data (alldata)
```

8.1.15 create_nscore_lookup

8.1.16 create_nscore_lookup_old

8.1.17 csemivar_exp

```
 csemivar_exp : Calculate experimental cross semivariogram

[hc,garr,h,gamma,hangc,head,tail]=semivar_exp(pos1,val1,pos2,val2,nbin,nbinang)

 pos1 : [ndata,ndims] : attribute 1
 val1 : [ndata,1]     : attribute 1
 pos2 : [ndata,ndims] : attribute 2
 val2 : [ndata,1]       attribute 2

 nbin : [integer] number of bins on distance anxes
        [array] if specified as an array, this is used.

 nbinang : [integer] number of arrays between 0/180 degrees
                     (default 1)
 Example isotrop:
   [hc,garr]=semivar_exp(pos1,val1,pos2,val2);
   plot(garr,hc);

 Example directional [0,45,90,135,180]:
   [hc,garr,h,gamma,hangc]=semivar_exp(pos1,val1,pos2,val2,20,4);
   plot(garr,hc);
   legend(num2str(hangc'))


 TMH/2005
```

8.1.18 deformat_variogram

```
deformat_variogram : convert gstat variogram line into matlab structure

Call:
  V=deformat_variogram(txt);
```

```
 Example:
 V=deformat_variogram('1 Sph(2)')

V =

     par1: 1
     par2: 2
     type: 'Sph'
    itype: 1


 See also : format_variogram

 TMH /2004
```

8.1.19 dual

```
```

8.1.20 edist

```
 edist : Euclidean distance

 Call :
   D=edist(p1,p2,transform,isorange)

 p1,p2 : vectors

 transform : GSTAT anisotropy and/or range information

 isorange : [0] (default), transform is the usual GSTAT-anisotropy setting
 isorange : [1] means that transform simply lists the range in
 each dimensions, and that no rotation is performed
```

8.1.21 estim_taran

```
 estim_taran, one data set : Tarantola equations (16-17)

 CALL : [m_est,Cm_est]=estim_taran(G,Cm,Cd,m0,d0);
```

8.1.22 etype

```
```

8.1.23 f77strip

```
 f77strip : Strips f77 characters from binary file.

 [data]=f77strip(file,format,xskip,zskip);

 IN :
 required
 file [string], optional, deafult='f77.bin'
```

```
optional :
format [string], 'float16','float32'[default],'float64'
xskip [scalar], Skip every xskip column
zskip [scalar], Skip every zskip row

OUT
data [matrix], required

Purpose : Reads a f77 style binary file

At the beginning and end of each row, an integer
containing the number of bytes in the row is printed
(like ftnunstrip/ftnstrip in the CWP SU package)

by Thomas Mejer Hansen, 05/2000
Octave 2.0.15 and Matlab 5.3 compliant
```

8.1.24 fft_ma_3d

```
The FFT-MA algorithm in 3D
Call: out=FFT_MA_3D(ny,nx,nz,Nly,Nlx,Nlz,cell,h_min,h_max,h_z,gmean,gvar,it)
it: 1) Spherical, 2) Exponential, 3) Gaussian
ny, nx, nz: Number of model parameters in the x, y, and z directions,
respectively
Nlx, Nly, Nlz: Extensions of the grid in the x, y, and z directions in
order to avoid artefacts due to edge effects. Number of model parameters
in the extension = Nlx*range_x/cell, where cell is the size of the cells
and range_x is the range i the x-direction.
h_min, h_max, and h_z, are the ranges in the horizontal (x), vertical (y) and (z)  ↩
    direction.
gvar: Global variance
gmean: Global mean
```

8.1.25 format_variogram

```
format_variogram : Convert matlab style Variogram to Gstat style

Call :
  txt=format_variogram(V);

See also: deformat_variogram
```

8.1.26 fresnel_punch

```
fresnel_punch : computes the sensitivity kernel for a wave traveling from S to R.

CALL :
   [K,RAY,timeS,timeR,raypath]=fresnel_punch(Vel,x,y,z,S,R,freq,alpha);

IN :
   Vel : Velocity field
   x [1:nx] :
   y [1:ny] :
```

```
   z [1:nz] :
   S [1,3] : Location of Source
   R [1,3] : Location of Receiver
   freq : frequency
   alpha: controls exponential decay away ray path

OUT :
   K : Sensitivity kernel
   R : Ray sensitivity kernel (High Frequency approx)
   timeS : travel computed form Source
   timeR : travel computed form Receiver
   raypath [nraydata,ndim] : the center of the raypath

TMH/2006
```

8.1.27 gaussian_simulation_cholesky

```
gaussian_simulation_cholesky : generate realizations from a Gaussian 2D
distribution mean m0 and covariance Cm

Very eficient for smaller models to generate a sample
of the posterior PDF for least squares inversion problems :

For example :
 [m_est,Cm_est]=least_squares_inversion(G,Cm,Cd,m0,d0);
 z_uncond=gaussian_simulation_cholesky(m_est,Cm_est,nsim);
 z_cond=gaussian_simulation_cholesky(m_est,Cm_est,nsim);

Choleksy decomposition can be calculated prior to calling
  Cm=chol(Cm);
  is_chol=1;
  z_cond=gaussian_simulation_cholesky(m_est,Cm_est,nsim,is_chol);



% unconditional realization:
x=[1:1:40];
y=[1:1:40];
[xx,yy]=meshgrid(x,y);
Cm=precal_cov([xx(:) yy(:)],[xx(:) yy(:)],'1 Sph(45,.1,30)');
m0=xx.*0;
nsim=12;
[z_uncond,D]=gaussian_simulation_cholesky(m0,Cm,nsim);
for i=1:nsim;subplot(4,3,i);imagesc(x,y,D(:,:,i));axis image;end


see also gaussian_simulation_cholesky_resim
```

8.1.28 gstat

```
gstat : call gstat from Matlab

CALL : gstat(G)
   G : gstat data structure OR gstat parameter file on disk

       [pred,pred_var,pred_covar,mask,G]=gstat(G)
```

8.1.29 gstat_binary

```
gstat_binary : returns the path to the binary gstat

Call :
   gstat_bin = gstat_binary;
```

8.1.30 gstat_convert

```
gstat_convert : convert between ascii/binary formats

 CALL : [data,x,y,dx,nanval]=gstat_convert(file,f,suf)
```

8.1.31 gstat_krig

```
gstat_krig : Simple/Ordinary Kriging using GSTAT

Call :
[d_est,d_var]=gstat_krig(pos_known,val_known,pos_est,V,options);

ndata : number of data observations
ndims : dimensions of data location (>=1)
nest  : number of data locations to be estimated

pos_known [ndata,ndims] : Locations of data observations
val_known [ndata,1 or 2]  : col1 : Data value as measured at 'pos_known'
                            col2 : Data uncertainty as measured at
                            'pos_known' (optional)
pos_est   [nest ,ndims] : Location of data to be estimated
V : Variogram model, e.g. '1 Sph(100)'


%% Example 1 : 1D - NO DATA UNCERTAINTY
profile on
pos_known=10*rand(10,1);
val_known=rand(size(pos_known)); % adding some uncertainty
pos_est=[0:.01:10]';
V=deformat_variogram('1 Sph(1)');
[d_est,d_var]=gstat_krig(pos_known,val_known,pos_est,V);
plot(pos_est,d_est,'r.',pos_est,d_var,'b.',pos_known,val_known(:,1),'g*')
legend('SK estimate','SK variance','Observed Data')
title(['V = ',V])
profile viewer



%% Example 2 : 1D - Data Uncertainty
pos_known=[1;5;10];
val_known=[0 3 2;0.001 1 0.001]'; % adding some uncertainty
pos_est=[0:.01:10]';
V='1 Sph(2)';
[d_est,d_var]=gstat_krig(pos_known,val_known,pos_est,V);
```

```
plot(pos_est,d_est,'r.',pos_est,d_var,'b.',pos_known,val_known(:,1),'g*')
legend('SK estimate','SK variance','Observed Data')
title(['using data uncertainty, V = ',V])


%% Example 3 : 2D estimation
pos_known=[0 1;5 8;10 1];
val_known=[0 3 2]';
x=[0:.1:10];
y=[0:.1:10];
[xx,yy]=meshgrid(x,y);
pos_est=[xx(:) yy(:)];
V='1 Sph(7)';
[d_est,d_var]=gstat_krig(pos_known,val_known,pos_est,V);
subplot(1,2,1);scatter(pos_est(:,1),pos_est(:,2),10,d_est)
axis image;title('Kriging mean')
subplot(1,2,2);scatter(pos_est(:,1),pos_est(:,2),10,d_var)
axis image;title('Kriging variance')


%% Example 4 :SIMULATION
pos_known=[0 1;5 1;10 1];
val_known=[0 3 2]';
pos_est=linspace(-1,11,200)';pos_est(:,2)=1;
V='.0001 Nug(0) + .2 Gau(2)';
[d_est,d_var]=gstat_krig(pos_known,val_known,pos_est,V);
plot(pos_est(:,1),d_est,'k-',pos_known(:,1),val_known(:,1),'r*')

options.nsim=120;
[d_sim,d_varsim,pos_sim]=gstat_krig(pos_known,val_known,pos_est,V,options);
d=sortrows([pos_sim(:,1) d_sim],1);
d_sim=d(:,2:(options.nsim+1));

d=sortrows([pos_sim(:,1) d_varsim],1);
d_varsim=d(:,2);

plot(pos_est(:,1),d_sim,'r-');

hold on
plot(pos_est(:,1),d_est,'k-','linewidth',4)
plot(pos_known(:,1),val_known(:,1),'b.')

plot(pos_est(:,1),d_varsim-4,'k-')
plot(pos_est(:,1),d_var-4,'r-')
hold off
```

8.1.32 gstat_krig_blinderror

```
gstat_krig_blinderror : blind cross validation using gstat

Call as gstat_krig is called :
   [d_est,d_var,be,d_diff]=gstat_krig_blinderror(pos_known,val_known,pos_est,V,options);

[d_est,d_var] : Cross validation prediction
[be] : Cross validation error

/TMH 12/2005
```

8.1.33 hpd_2d

```
hpd_2d : highest posterior density

call :
   [levels]=hpd_2d(lik,hpd_level)cl

lik=abs(peaks);
levels=hpd_2d(lik,[.1:.2:.9])
contourf(lik,levels)
```

8.1.34 hpd_2d_point

```
hpd_2d_point : highest posterior density plot from scattered data

Call :
 [lik,levels,x,y]=hpd_2d_point(x_p,y_p,lik_p,x,y,hpd_levels,corner_type)

See also : hpd_2d

Example :
 nd=1300;
 x_p=randn(nd,1)*1;
 y_p=randn(nd,1)*1;
 lik_p = abs(peaks(x_p,y_p));
 subplot(1,3,1);
 [lik,levels,x,y]=hpd_2d_point(x_p,y_p,lik_p);
 subplot(1,3,2);
 [lik,levels,x,y]=hpd_2d_point(x_p,y_p,lik_p,[],[],[.1:.1:1]);
 subplot(1,3,3);
 [lik,levels,x,y]=hpd_2d_point(x_p,y_p,lik_p,-1:.1:1,-1:.1:1,[.2 0.5 1.0]);
```

8.1.35 icpdf

```
icdf : inverse cimulative density function

find data value associated to an pk quantile.

CALL : d_obs=icdf(data,pk_obs)
```

8.1.36 indicator_transform_con

```
indicator_transform_con : transform continous data into indicator

CALL :

[id,lev]=indicator_transform_con(d,lev)

[d] : data
[lev] : indicator transform of list lev#s : Prob(zi<lev(i))
```

```
        if not specified level is chosen to match qantiles
        .1,.2,...,.9
```

8.1.37 indicator_transform_dis

```
indicator_transform_dis : transform discrete data into indicator

CALL :

[id,lev]=indicator_transform_dis(d,ident)

[d] : data
[ient] : Transform data into a binary discrete data, such that Prob(zi=ident(i))
        if not specified level is chosen all unique4 discrete
        identifiers are chosen.
```

8.1.38 inscore

```
inscore : normal score BACK transform

CALL :
  d=inscore(d_nscore,o_nscore)

d_nscore : normal score values to be back transformed
           using the ’o_nscore’ object, obtained using
           ’nscore’

See also nscore.m
```

8.1.39 isorange

```
isorange : convert range scaling to gstat/gslib range settings


for example
  V = ’1.0 Sph(0.7,0.8,0.9)’;

  Vgstat=isorange(V);
  format_variogram(Vgstat,1)

Used when ’options.isorange=1’
```

8.1.40 krig

```
krig : Simple/Ordinar/Trend Kriging

Call :
[d_est,d_var,lambda,K,k,inhood]=krig(pos_known,val_known,pos_est,V,options);

ndata : number of data observations
```

```
ndims : dimensions of data location (>=1)
nest  : number of data locations to be estimated

pos_known [ndata,ndims] : Locations of data observations
val_known [ndata,1 or 2]  : col1 : Data value as measured at 'pos_known'
                            col2 : Data uncertainty as measured at
                            'pos_known' (optional)
pos_est   [N ,ndims] : Location of N data locations to be estimated
V : Variogram model, e.g. '1 Sph(100)'
val_0 : A priori assumed data value (default=mean(val_known))



Example 1D - NO DATA UNCERTAINTY
profile on
pos_known=10*rand(10,1);
val_known=rand(size(pos_known)); % adding some uncertainty
pos_est=[0:.01:10]';
V=deformat_variogram('1 Sph(1)');
[d_est,d_var]=krig(pos_known,val_known,pos_est,V);
plot(pos_est,d_est,'r.',pos_est,d_var,'b.',pos_known,val_known(:,1),'g*')
legend('SK estimate','SK variance','Observed Data')
%title(['V = ',V])
profile viewer

See source code for more examples


see also : krig_npoint, krig_blinderror
```

8.1.41 krig_blinderror

```
krig_blinderror : Cross validation blind error
CALL :
  [d_est,d_var,be,d_diff,L,L2]=krig_blinderror(pos_known,val_known,pos_est,V,options, ↩
      nleaveout)
```

8.1.42 krig_covar_lik

```
krig_covar_lik : Calculates the likelihood tha V is consistent with data observations

Call :
  L=krig_covar_lik(pos_known,val_known,V,options)


Can be used to infer covariance properties (range, sill, anisotropy,...)
```

8.1.43 krig_crossval_1d_exh

```
krig_crossval_1d_exh
CALL :
  [V_L,B_be,ML,Mbe,ML2,par2_range,nugfrac_range]=krig_crossval_1d_exh(pos_known,val_known ↩
      ,V,options);
```

```
function [V_L,V_be,ML,Mbe,ML2,par2_range,nugfrac_range]=krig_crossval_1d_exh(pos_known, ↩
    val_known,V,options);
```

8.1.44 krig_npoint

```
krig_npoint : as 'krig' butfor multiple estimation position.

[d_est,d_var,options]=krig_npoint(pos_known,val_known,pos_est,V,options);

As krig, but allowing size(pos_known,1)>1

See also : krig
```

8.1.45 krig_optim_1d_exh

```
krig_optim_1d_exh
CALL :
  [V_L,B_be,ML,Mbe,ML2,par2_range,nugfrac_range]=krig_optim_1d_exh(pos_known,val_known,V, ↩
      options);
```

8.1.46 krig_optim_mcmc

```
krig_optim_mcmc
CALL :
  [V_new,be_acc,L_acc,par2,nugfrac_acc,V_acc,options]=krig_optim_mcmc(pos_known,val_known ↩
      ,V,options)
```

8.1.47 krig_optim_ml

```
krig_optim_ml : MCMC Maximum likelihood optimization

Call :

   [Vop2,Vop1,be,L,par2,nugfrac,Vall]=krig_optim_ml(pos_known,val_known,V,options)
```

8.1.48 krig_optim_range

```
krig_optim_range
CALL :
  [V,be]=krig_optim_range(pos_known,val_known,V,options)
```

8.1.49 krig_volume

```
krig_volume : kriging with volume average data

See hansen et. al. 2005.
```

8.1.50 least_squares_inversion

```
least_squares_inversion, one data set : Tarantola equations (16-17)

CALL : [m_est,Cm_est]=least_squares_inversion(G,Cm,Cd,m0,d0);

See also : gaussian_simulation_cholesky
```

8.1.51 least_squares_oneone

```
least_squares_oneone : Least squares inverison using only scalar
                       operations. (only valid when offdiag(Cd)=0)

See Tarantola (2005), Inverse Problem Theory, page 198, Ch 6.

Call :
  [m_est,sigma2,Cm_est]=least_squares_oneone(G,Cm,Cd,m0,d_obs)
```

8.1.52 least_squares_partition_data

```
least_squares_partition_data : least sq. inversion using partitioning

See Tarantola (2005), page 197, eqn. 6.211 or 6.212.

Least squares inversion by partitioning into to data subsets
with independent data covariance !
This can be very fast if the number of data observations is
large, and large compared to the number of model parameters.


CALL : [m_est,Cm_est]=least_squares_partition_data(G,Cm,Cd,m0,d_obs,nsubsets,use_eq);
```

8.1.53 least_squares_slice

```
least_squares_slice : least sq. inversion using partitioning


CALL : [m_est,Cm_est]=least_squares_slice(G,Cm,Cd,m0,d0,id,im);
```

8.1.54 mgstat_clean

```
mgstat_clean : clean up temporary files from visim, sgems, fast
```

8.1.55 mgstat_demo

```
mgstat_demo : demos illustrating the use of mGstat

Try some of the following demos:

mgstat_demo('mgstat'); % mgstat demo, illustrating the native matlab
                       %  algorithms
mgstat_demo('gstat');  % demos using gstat
mgstat_demo('visim');  % demos using visim
mgstat_demo('sgems');  % demos using sgems
mgstat_demo('snesim'); % demos using snesim

mgstat_demo('all'); % runs all of the available demos.
```

8.1.56 mgstat_dir

```
mgstat_dir : return the install directory for mGstat
```

8.1.57 mgstat_set_path

```
mgstat_set_path : set path to all mGstat

  set path to :
    mGstat_Install_Dir/snesim
    mGstat_Install_Dir/visim
    mGstat_Install_Dir/sgems
    mGstat_Install_Dir/fast
    mGstat_Install_Dir/misc
```

8.1.58 mgstat_verbose

```
mgstat_verbose : list verbose information to the console

Call:
 mgstat_verbose(txt,verbose)

txt [string] : text to be displayed
verbose [integer] (def=0) : increase to see more information

'vlevel' must be set in the mgstat_verbose.m m-file.

All entries with vebose>vlevel are displayed
```

8.1.59 nanmean

```
nanmean : mean of data, ignoring NaN's

call : meandata=nanmean(data)
```

```
data [n-dimensional array]
meandata [scalar]

TMH(tmh@gfy.ku.dk), 2001
```

8.1.60 nanstd

```
nanstd : std of data, ignoring NaN's

call : stddata=nanstd(data)

data [n-dimensional array]
stddata [scalar]

TMH(tmh@gfy.ku.dk), 2001
```

8.1.61 nanvar

```
nanvar : var of data, ignoring NaN's

call : vardata=nanvar(data)

data [n-dimensional array]
vardata [scalar]

TMH(tmh@gfy.ku.dk), 2001
```

8.1.62 nhood

```
nhood : Neighborhood selection


TMH/2005
```

8.1.63 normcdf

```
NORMCDF returns normal cumulative distribtion function

cdf = normcdf(x,m,s);

Computes the CDF of a the normal distribution
   with mean m and standard deviation s
   default: m=0; s=1;
x,m,s must be matrices of same size, or any one can be a scalar.

see also: NORMPDF, NORMINV
```

8.1.64 norminv

```
NORMINV returns inverse cumulative function of the normal distribution

x = norminv(p,m,s);

Computes the quantile (inverse of the CDF) of a the normal
   cumulative distribution with mean m and standard deviation s
   default: m=0; s=1;
p,m,s must be matrices of same size, or any one can be a scalar.

see also: NORMPDF, NORMCDF
```

8.1.65 normpdf

```
NORMPDF returns normal probability density

pdf = normpdf(x,m,s);

Computes the PDF of a the normal distribution
   with mean m and standard deviation s
   default: m=0; s=1;
x,m,s must be matrices of same size, or any one can be a scalar.

see also: NORMCDF, NORMINV
```

8.1.66 nscore

```
nscore : Normal score transform

CALL :
  [d_nscore,o_nscore]=nscore(d,w1,w2,dmin,dmax,DoPlot)


INPUT PARAMETERS :
Required :
d : array of data to transformed into normal scorres.

Optional :
w1,dmin : Extrapolation options for lower tail.
          w1=1 -> linear interpolation
          w1>1 -> Gradual power interpolation
w2,dmax : Extrapolation options for lower tail.
          w1=1 -> linear interpolation
          w1<1 -> Gradual power interpolation

See Goovaerts page 280-281 for details

DoPlot : ==1 --> The choice of CCPDF to be used for normal score
                 transformation is plotted
OUTPUT PARAMETERS

d_nscore : normal score transform of input data
o_nscore : normal socre object containing information
           needed to perform normal score backtransform.


See also : inscore
```

8.1.67 plot_scale

```
plot_scale : plot scale to figure

Call:
   plot_scale(ax,len,pos,FontSize)

   ax: axis (gca)
   len [1,2]: length of scale length in each direction
   pos [1],[2],[3] or [4]: Position of scale plot.
       [NW],[SW],[NE],[SE]


Example
       imagesc(peaks);
       hold on;
       plot_scale(gca,[15 15],3);
       hold off;
       axis image
```

8.1.68 pos2index

```
[ix,iy]=pos2index(xpos,ypos,x,y);
```

8.1.69 ppp

```
file=ppp.m : Creates a lx,ly cm plot

call function ppp(lx,ly,Fsize,x1,y1),

(lx,ly) : WIDTH and HEIGHT of plot in cm
Fsize   : Font Size
(x1,y1) : Lower left corner of plot (relative to lower left corner of paper)


(C) Thomas Mejer Hansen, 1997-2001, tmh@gfy.ku.dk
```

8.1.70 precal_cov

```
precal_cov : Precalculate covariance matrix

CALL :
  cov=precal_cov(pos1,pos2,V,options);

pos1   [ndata1,ndims] : Location of data to be estimated
pos2   [ndata2,ndims] : Location of data to be estimated
V [struct] : Variogram structure

cov [ndata1,ndata1] : Covariance matrix
```

```
Ex:
x=[1:1:10];
y=[1:1:20];
[xx,yy]=meshgrid(x,y);
cov=precal_cov([xx(:) yy(:)],[xx(:) yy(:)],'1 Sph(5,.1,0)');
```

8.1.71 print_mul

```
print_mul : prints both EPS and PNG figures of current plot


Call :
  print_mul('test') : prints test.eps and test.png

In case 'mogrify' is available on the system
the png file will be trimmed and optionall
A specific color will be made transparent :

  print_mul('test',red)
      also creates trim_test.png

  print_mul('test',1)
      also creates trim_test.png, with transparent white color

  print_mul('test','red')
      also creates trim_test.png, with transparent red color

/TMH 12/2005
```

8.1.72 progress_txt

```
progress_txt : console based progress bar

Ex1 :
  for i=1:10000;
    progress_txt(i,10000,'Ciao');
  end

Ex1 :

  for i=1:10;
  for j=1:10;
  for k=1:10;
    progress_txt([i j k],[10 100 1000],'i','j','k');
  end
  end
  end

TMH/2005, thomas@cultpenguin.com
```

8.1.73 rank_transform

```
rank_transform : rank transform data

Call :
  [r]=rank_transform(d);
```

8.1.74 read_arcinfo_ascii

```
read_arcinfo_ascii : Reads ascii formatted ArcInfo files

Call :
  [data,x,y,dx,nanval,x0,y0,xll,yll]=read_arcinfo_ascii(filename);
```

8.1.75 read_bin

```
read_bin : Reads a binary file to matlab

CALL : function [dataout]=read_bin(fileid,nx,nz,fchar,format,b_order)

REQUIRED
  fileid
  nx

OPTIONAL
  nz      : Number of samples in 2nd direction
  fchar (scalar)  : (==1)Remove F77 chracters
  format (string) : ’float32’ [default] or ’int16’ or ’int32’,...
  b_order : set byteorder : ’0’ : Little Endian
                            ’1’ : Big endian


/TMH 2006
```

8.1.76 read_eas

```
read_eas : reads an GEO EAS formatted file into Matlab.

Call [data,header,title]=read_eas(filename);

TMH (tmh@gfy.ku.dk)
```

8.1.77 read_emm

```
read_emm : read emm output file from em1dinv

CALL :
  [emm]=read_emm(filename);
```

8.1.78 read_gstat_ascii

8.1.79 read_gstat_par

```
read_gstat_par : Reads gstat.par file into Matlab data structure

CALL :
   G = read_gstat_par('ex01.cmd');

KNOWN BUGS (FEB 2004)
  Cannot load covariogram : covariogram(data1,data2)
  Semivariogram line : Can only contain veriogram, not filename
```

8.1.80 read_gstat_semivar

8.1.81 read_petrel

```
read_peterl : reads an PETREL ascii point file

Call [data,header]=read_eas(filename);

TMH (tmh@gfy.ku.dk)
```

8.1.82 read_punch_par

```
FUNCTION : [fxs,fys,fzs,nx,ny,nz,x0,y0,z0,h,timefile,velfile,reverse,maxoff]= ↩
    read_punch_par(filename);
Purpose : Reads PAR file from PUNCH program (HOLE PROGRAM)

TMH 09/1999;
```

8.1.83 read_surfer_grid

```
read_surfer_grid : Read Surfer ASCII GRD file

CALL :
[data,x,y]=read_surfer_grid(filename);

IN:
  filename [char] :string
OUT:
  data [ny,nx]
  x [nx]
  y [ny]
```

8.1.84 rot2

```
rot2 : 2D coordiante transformation

Call :
  htrans=rot2(h,ang,ani,dir)

h :[hx,hy] location
ang : angle in radians
ani : anisotropy factor

dir : 'direction' =1, normal transform, <>1, inverse transform


TMH/2005
```

8.1.85 scatter_dot

```
scatter_dot : A black dot beneith scatter dots

Call  :
  scatter_dot(x,y,MS,v,option)
```

8.1.86 scatter_hpd

```
scatter_hpd : calculate 2D HPD region

[prob,levels,x_arr,y_arr,f2,c2]=scatter_hpd(x,y,p,p_levels,x_arr,y_arr)
```

8.1.87 semivar

```
semivar : calcualte semivariogram

[binc,sv,bin_array,svM]=semivar(loc,val,bin_array);

loc : [ndim,n]
```

8.1.88 semivar_exp

```
 semivar_exp : Calculate experimental variogram

[gamma,h,ang_center,gamma_cloud,h_cloud]=semivar_exp(pos,val,nbin,nbinang)

 pos : [ndata,ndims]
 val : [ndata,ndata_types]

 nbin : [integer] number of bins on distance anxes
        [array] if specified as an array, this is used.
```

```
nbinang : [integer] number of arrays between 0/180 degrees (def=1)
          [array] array of angles.

Example : load jura data
  dwd=[mgstat_dir,filesep,'examples',filesep,'data',filesep,'jura',filesep];
  [p,pHeader]=read_eas([dwd,'prediction.dat']);
  idata=6;dval=pHeader{idata};
  pos=[p(:,1) p(:,2)];
  val=p(:,idata);
  figure;scatter(pos(:,1),pos(:,2),10,val(:,1),'filled');
    colorbar;title(dval);xlabel('X');ylabel('Y');axis image;

Example isotrop:
  [garr,hc]=semivar_exp(pos,val);
  plot(hc,garr);
  xlabel('Distance (m)');ylabel('semivariance');title(dval)

Exmple directional
  [garr,hc,hangc,gamma,h]=semivar_exp(pos,val,20,4);
  plot(hc,garr);
  legend(num2str(180*hangc'./pi))
  xlabel('Distance (m)');ylabel('semivariance');title(dval)
```

8.1.89 semivar_exp_gstat

```
semivar_exp_gstat : Experimental semivariance using GSTAT

CALL :

[gamma,hc,np,av_dist]=semivar_exp_gstat(pos,val,angle,tol,width,cutoff)

IN :
   pos : [ndata,ndims] : location of data
   val : [ndata,1] : data values
   angle [1] : angle (degrees)
   tol [1] : angle tolerance around 'angle' (degrees)
   width[1] : width of bin use to average semivariance
   cutoff[1] : max distance for whoch to compute semivariance



'angle' and 'tol' are optional

defults: angle=0;
         tol=180

OUT :
   gamma : semivariance
   hc : Seperation distance
   np : Number of points for each seperation distance
   av_dist : Average distance

EXAMPLE :
  % GET JURA DATA
  dwd=[mgstat_dir,filesep,'examples',filesep,'data',filesep,'jura',filesep];
  [p,pHeader]=read_eas([dwd,'prediction.dat']);
  idata=6;dval=pHeader{idata};
```

```
    pos=[p(:,1) p(:,2)];
    val=p(:,idata);
    figure;scatter(pos(:,1),pos(:,2),10,val(:,1),'filled');
      colorbar;title(dval);xlabel('X');xlabel('Y');axis image;

    % ISOTROP SEMIVARIOGRAM
    [gamma,hc]=semivar_exp_gstat(pos,val);
    figure;plot(hc,gamma);
    title(dval);xlabel('Distance (m)');ylabel('Semivariance');

    % ANISOTROPIC SEMIVARIOGRA
    hang=[0 45 90];
    tol=10; % Angle tolerance
    clear gamma;
    figure
    for ih=1:length(hang);
       [gamma(:,ih),hc]=semivar_exp_gstat(pos,val,hang(ih),tol);
    end
    figure;plot(hc,gamma);
    title(dval);xlabel('Distance (m)');ylabel('Semivariance');
    legend(num2str(hang'));

    % ANISOTROPIC SEMIVARIOGRAM (2)
    width=[0.1];
    cutoff=[4];
    hang=[0 45 90];
    tol=10; % Angle tolerance
    clear gamma;
    for ih=1:length(hang);
       [gamma,hc]=semivar_exp_gstat(pos,val,hang(ih),tol,width,cutoff);
       p(ih)=plot(hc,gamma);hold on
       if ih==1, set(p(ih),'color',[0 0 0]);end
       if ih==2, set(p(ih),'color',[0 1 0]);end
       if ih==3, set(p(ih),'color',[0 0 1]);end
    end
    hold off
    title(dval);xlabel('Distance (m)');ylabel('Semivariance');
    legend(num2str(hang'));
```

8.1.90 semivar_map

```
semivar_map : create 2D semivariogram map

See Goovaerts, p. 99
```

8.1.91 semivar_optim

8.1.92 semivar_synth

```
semivar_synth : synthethic semivariogram

[sv,d]=semivar_synth(V,d,gstat);
   V : Variogram model
   d : seperation (array or matrix)
   gstat : [0] use SGeMS semivariogram definitions (default)
   gstat : [1] use GSTAT semivariogram definitions


Call ex :
   [sv,d]=semivar_synth('0.1 Nug(0) + 1 Gau(1.5)',[0:.1:6]);plot(d,sv)
or :
   V(1).par1=1;V(1).par2=1.5;V(1).type='Gau';
   V(2).par1=0.1;V(2).par2=0;V(2).type='Nug';
   [sv,d]=semivar_synth(V,[0:.1:6]);plot(d,sv)
```

8.1.93 set_mgstat_path

8.1.94 sgsim

```
sgsim : sequential Gaussian simulation

Call :
  [sim_mul]=sgsim(pos_known,val_known,pos_sim,V,options);%

all arguments are the same as for 'krig.m', except the number of
generated realizations can be set using :
   options.nsim=10; (default is options.nsim=1)

note: this algorithm is very slow and for teaching purposes
      if you intend to simulate large fields use either the
      'gstat' or 'mgstat' simulation options.


see also: krig
```

8.1.95 space2char

```
space2char : replace oen character with another in string

txtout=space2char(txt,charout,charin);

Example :
   txt='Hello nice world';
   space2char(txt)
           ans = Hello_nice_world
   space2char(txt,'+')
           ans = Hello+nice+world
   space2char(txt,'+','l')
           ans = He++o nice wor+d
```

8.1.96 spherical_spreading

```
sperical_spreading(r,type);
```

8.1.97 strip_space

```
 strip_space : strip leading/tailing spaces from string

 CALL :
   txt=strip_space(txt,type);

   txt[string]
   type[integer] : [0] strip leading and trailing space (default);
   type[integer] : [1] strip leading space;
   type[integer] : [2] strip trailing space;


 EX :
  a='    Hei Ho Here We Go      ';
 ['''',strip_space(a),'''']
 ans =
 'Hello World'

% strip leading space
 ['''',strip_space(a,1),'''']
% strip trailing space
 ['''',strip_space(a,2),'''']
```

8.1.98 suptitle

```
 suptitle : Puts a title above all subplots.
 SUPTITLE('text') adds text to the top of the figure
 above all subplots (a "super title"). Use this function
 after all subplot commands.
```

8.1.99 title_alt

```
 title_alt : Alternate title positioning

 Call :
    title_alt(string,isub,location,dw,w_out)

 title     [str] : title string
 isub      [int] : Number of subplot. 1-->'a)' is prepended to the title
                                      2-->'b)' is prepended to the title..
                                      0--> use original string [Default]
 location  [str] : 'NorthWestInside'
                   'NorthWestOutside' [Default]
                   'NorthEastInside'
                   'NorthEastOutside'

 dw        [rea] : distance from edge to label, relative to plot size
                   [default dw=0.01];

 w_out     [rea] : distance from edge to horizontal edge of label,
                   when location='*Outsize', relative to plot size.
                   [default dw=0.2];



 EXAMPLE :
   figure
   for i=1:5;
       subplot(2,3,i)
       imagesc(peaks(i*10))
       title_alt('Title',i);
   end

   figure
   subplot(2,2,1);title_alt('NorthWestInside',i,'NorthWestInside');
   subplot(2,2,2);title_alt('NorthWestOutside',i,'NorthWestOutside');
   subplot(2,2,3);title_alt('NorthEastInside',i,'NorthEastInside');
   subplot(2,2,4);title_alt('NorthEastOutside',i,'NorthEastOutside');

 (C) TMH/2007
```

8.1.100 vonk2d

```
VONK2D.M : 2D Von Karman Distribution

Call : [randdata,x,z,data,expcorr]=vonk2d(rseed,dx,dz,ax,az,ix,iz,pop,med,nu,vel,frac)

rseed : Random Seed number
dx,dz : Spatial distance
ax,az : Horizontal, vertical lengthscale
ix,iz : size of model in same scale as ax,az
nu    : Hurst Number

pop   : Population, [1]:Gaussian [2]:PDF
med   : Medium    , [1]:Gaussian [2]:Exponential [3]: Von Karman
                    [4]:Pink     [5]:Brown
vel   : Scalar or vector of velocities, For pop=pdf,v(1) is used as
                                        +/-max velocity of input field
frac  : fraction assigned to each velocity (normalized), same size
        as vel

(C) 1998-2001 Thomas Mejer Hansen (tmh@gfy.ku.dk)
UPDATED APR 05 1999 /TMH
Octave 2.0.15 and Matlab 5.3 compliant
```

8.1.101 watermark

```
watermark : _add watermark to figure : watermark(txt,FontSize);

Call
 watermark(txt);
 watermark(txt,FontSize);
 ax=watermark(txt,FontSize,position);
```

8.1.102 write_arcinfo_ascii

```
write_arcinfo_ascii : Writes ascii formatted ArcInfo files

CALL :
```

```
[data,x,y,dx,nanval]=write_arcinfo_ascii(filename,data,x,y,nannumber,xll,yll);

filename [char] :string
data [ny,nx]
x [nx]
y [ny]
nannumber [1] : can be left empty []. Optional.
xll [char] : 'CENTER'(def) or 'CORNER'. Optional.
yll [char] : 'CENTER' or 'CORNER'. if 'xll' is set, yll=xll.
```

8.1.103 write_bin

```
write_bin.m

 CALL :
   write_bin(filename,variable,fchar,format,b_order);

 REQUIRED :
   filename (string)
   variable : to be written to a binary file;

 OPTIONAL
   fchar (scalar)  : [1] Remove F77 chracters [0,defailt] do nothing
   format (string) : 'float32' [default] or 'int16' or 'int32',...
   b_order : set byteorder : '0' : Little Endian
```

8.1.104 write_eas

```
write_eas : writes a GEO EAS formatted file into Matlab.

Call write_eas(filename,data,header,title,nanValue);

filename [string]
data [ndata,natts]
header [structure{natts}] : header values for data columns
title [string] : optional title for EAS file
nanValue [float] : NaN value

TMH (tmh@gfy.ku.dk)
```

8.1.105 write_gstat_ascii

8.1.106 write_gstat_par

```
write_gstat_par : write gstat.par file from Matlab structure

CALL :

   filename=write_gstat_par(G,filename);

 input --:
 G [struct]: gstat matlab structure
 filename [string] : optinal filename

 output --:
 filename [string] : filename of command file written to disk
```

8.1.107 write_punch_par

```
write_punch_par(filename,timefile,velfile,fxs,fys,fzs,nx,ny,nz,x0,y0,z0,h,reverse,maxoff) ↩
    ;
Purpose : WRITES OUT PAR-FILE FOR USE WITH 'PUNCH' (John Hole)

CALL write_punch_par(filename,timefile,velfile,fxs,fys,fzs,nx,ny,nz,x0,y0,z0,h,reverse, ↩
    maxoff);
 filename [string] : Name of par-file
 timefile [string] : Name of output-time file
 velfile  [string] : Name of input velocity file
 fxs      [scalar] :
 fys      [scalar] :
 fzs      [scalar] :
 nx       [scalar] :
 ny       [scalar] :
 nz       [scalar] :
 x0       [scalar] :
 y0       [scalar] :
 z0       [scalar] :
 h        [scalar] :
 reverse  [scalar] :
 maxxoff  [scalar] : Maximum offset

TMH 09/1999
```

8.1.108 write_surfer_grid

```
write_surfer_grid : Writes ascii formatted Surfer GRD file

CALL :
[data,x,y,dx,nanval]=write_surfer_grid(filename,data,x,y);

filename [char] :string
data [ny,nx]
x [nx]
y [ny]
```

8.2 VISIM functions

8.2.1 G_to_visim

8.2.2 calc_gstat_semivar

8.2.3 covar_prob

8.2.4 read_visim

8.2.5 semivar_mat

8.2.6 visim

8.2.7 visim_calc_semivar_prob

8.2.8 visim_cholesky

8.2.9 visim_clean

8.2.10 visim_error_sim

8.2.11 visim_format_variogram

8.2.12 visim_init

8.2.13 visim_lsq

8.2.14 visim_make_movie

8.2.15 visim_mask

8.2.16 visim_merge_volume_data

8.2.17 visim_movie

8.2.18 visim_plot

8.2.19 visim_plot_condtab

8.2.20 visim_plot_etype

8.2.21 visim_plot_hist

8.2.22 visim_plot_kernel

8.2.23 visim_plot_kernel2

8.2.24 visim_plot_rpath

8.2.25 visim_plot_semivar

8.2.26 visim_plot_semivar2

8.2.27 visim_plot_semivar_compare

8.2.28 visim_plot_semivar_mul

8.2.29 visim_plot_semivar_real

8.2.30 visim_plot_sim

8.2.31 visim_plot_stat

8.2.32 visim_plot_volfit

8.2.33 visim_plot_volume

8.2.34 visim_precal_linearization

8.2.35 visim_prior_prob

8.2.36 visim_prior_prob_gibbs

8.2.37 visim_prior_prob_mcmc

8.2.38 visim_prior_prob_mcmc_tomolin

8.2.39 visim_prior_prob_sill

8.2.40 visim_semivar

8.2.41 visim_semivar_pdf

8.2.42 visim_semivar_uncon

8.2.43 visim_set_broadband_covariance

8.2.44 visim_set_conditional_point

8.2.45 visim_set_multiscale_covariance

8.2.46 visim_set_resim_data

8.2.47 visim_setup_punch

8.2.48 visim_setup_tomo_kernel

8.2.49 visim_slice_volume

8.2.50 visim_to_G

8.2.51 visim_tomo_setup

8.2.52 visim_tomography

8.2.53 visim_tomography_forward

8.2.54 visim_tomography_linearize

8.2.55 vvisim

8.2.56 write_visim

8.3 SNESIM functions

8.3.1 read_snesim

8.3.2 snesim

8.3.3 snesim_init

8.3.4 snesim_prior_sampler

8.3.5 snesim_set_resim_data

8.3.6 write_snesim

8.4 S-GeMS functions

8.4.1 eas2sgems

8.4.2 sgems

8.4.3 sgems2eas

8.4.4 sgems_clean

8.4.5 sgems_demo

8.4.6 sgems_get_par

8.4.7 sgems_grid

8.4.8 sgems_grid_py

8.4.9 sgems_image2ti

8.4.10 sgems_plot_project

8.4.11 sgems_plot_structure

8.4.12 sgems_ppm

8.4.13 sgems_read

8.4.14 sgems_read_project

8.4.15 sgems_read_xml

8.4.16 sgems_set_resim_data

8.4.17 sgems_variogram_xml

8.4.18 sgems_write

8.4.19 sgems_write_grid

8.4.20 sgems_write_pointset

8.4.21 sgems_write_xml

8.5 FAST/nfd functions

8.5.1 eikonal_raylength

8.5.2 fast_demo

8.5.3 fast_fd_2d

8.5.4 fast_fd_2d_chunk

8.5.5 fast_fd_2d_traveltime

8.5.6 fast_fd_2d_traveltime_matrix

8.5.7 fast_fd_clean

8.5.8 fast_fd_write_par

8.5.9 test_fast_fd

8.6 Misc functions

8.6.1 LowPass1

8.6.2 LowPass1nan

8.6.3 LowPass2

8.6.4 LowPass2nan

8.6.5 accept_rate

8.6.6 caxis_squeeze

8.6.7 cmap_quantile

8.6.8 cmap_rwb

8.6.9 conv2_strip

8.6.10 conv_strip

8.6.11 despike

8.6.12 figure_focus

8.6.13 find_row_array

8.6.14 gamma_coefficients

8.6.15 gaussian_likelihood

8.6.16 generalized_gaussian

8.6.17 generalized_gaussian_2d

8.6.18 isoctave

8.6.19 jura

8.6.20 kernel_buursink_2d

8.6.21 kernel_finite_2d

8.6.22 kernel_fresnel_2d

8.6.23 kernel_fresnel_monochrome_2d

8.6.24 kernel_multiple

8.6.25 kernel_slowness_to_velocity

8.6.26 kml_line

8.6.27 kml_points

8.6.28 mspectrum

8.6.29 munk_fresnel_2d

8.6.30 munk_fresnel_3d

8.6.31 pick_first_arrival

8.6.32 plot_mh_error_hist

8.6.33 plot_mh_loglikelihood

8.6.34 punch

8.6.35 rayinv_grid_v

8.6.36 rayinv_load_tx

8.6.37 rayinv_load_v

8.6.38 rayinv_plot_tx

8.6.39 rickerwavelet

8.6.40 sample_generalized_gaussian

8.6.41 set_paper

8.6.42 set_resim_data

8.6.43 statusbar

8.6.44 su_write_model

8.6.45 test_fd_su_gpr