SIPPI

Ed. version 1.0

Contents

About

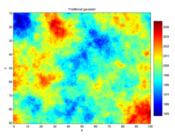
SIPPI is a Matlab toolbox (compatible with GNU Octave) that allow sampling the solution of non-linear inverse problems with realistic a priori information.

In order to make use of SIPPI one has to

- Install and setup SIPPI
- Define the prior model, in form of the prior data structure
- Define the forward model, in form of the forward data structure, and the sippi_forward.m m-file
- Define the data and noise model, in form of the prior data structure
- Choose a method for sampling the a posteriori probability density.

Chapter 1

Introduction



The latest version of SIPPI is available from Sourceforge

Chapter 2

Installation

2.1 SIPPI

Download the latest version of SIPPI from http://sippi.sourceforge.net.

Unpack ZIPPI_1.0.zip somewhere, for example to ’c:\Users\tmh\SIPPI’. Then setup the Matlab path to point to the appropriate SIPPI directories:

```
addpath c:\Users\tmh\SIPPI
sippi_set_path
```

2.1.1 SGeMS (optional)

To make use of the SISIM and SNESIM type priori models SGeMS needs to be available.

Currently only SGeMS version 2.1 (download) for Windows is supported.

Chapter 3

Setting up SIPPI

3.1 The a priori model

3.1.1 Types of a priori models

3.1.1.1 1D Generalized Gaussian

A 1D generalized Gaussian prior model can be specified using the 'gaussian' type prior model

```
prior{1}.type='gaussian';
```

A simple 1D Gaussian distribution with mean 10, and standard deviation 2, can be specified using

```
prior{1}.type='gaussian';
prior{1}.m0=10;
prior{1}.std=2;
```

The norm of a generalized Gaussian can be set using the 'norm' field. A generalized 1D Gaussian with mean 10, standard devation of 2, and a norm of 70, can be specified using (The norm is equivelent ot the beta factor referenced in Wikipedia:Generalized_normal_dist

```
prior{1}.type='gaussian';
prior{1}.m0=10;
prior{1}.std=2;
prior{1}.norm=70;
```

3.1.1.2 VISIM

3.1.1.3 FFTMA

3.1.1.4 SISIM

3.1.1.5 SNESIM

3.1.2 Sampling the prior

Once the prior data structure has been defined a sample from the prior distribution can be generated using

```
m=sippi_prior(prior);
```

'm' is a Matlab data structure of the same size as the 'prior' data structure. Thus, if two prior distributions have been defined in 'prior{1}' and 'prior{2}', then 'm{1}' will hold a realization of 'prior{1}', and 'm{2}' will hold a realization of 'prior{2}'.

Each time 'm=sippi_prior(prior)' is called, a new independant realization of the prior will be generated.

3.1.3 Sequential Gibbs sampling / Conditional Resampling

All the available a priori types available allow perturbing one realization of a prior into a new realization of prior, in the vicinity of the first one. To do this we make use of sequential Gibbs sampling [HCM12]. Sequential Gibbs in essence is a type of conditional resampling. From a current realization of a prior, a number of model parameters are discarded and treated as unknown, and the simulated conditional to the fixed values of the model parameters.

In order to generate a new realiztion 'm2' in the viciinity of the realization 'm1' use

```
m1=sippi_prior(prior);
[m2,prior]=sippi_prior(prior,m1);
```

If this process is iterated, then a random walk in the space of a priori acceptable models will be perform. And, the collection of realization obatined, will represent a sample from prior distribution.

3.1.3.1 Controlling sequential Gibbs sampling / Conditional Resampling

All properties related to sequential Gibbs sampling can be set in the 'seq_gibbs' data struture, for each prior type. The follwing two parameters determined how the a current model is perturbed

```
prior{m}.seq_gibbs.step=1;
prior{m}.seq_gibbs.type=2;
```

3.2 The data and the noise

3.3 The forward model

Chapter 4

The a posteriori distribution

4.1 Sampling the a posteriori probability density

4.1.1 The rejection sampler

4.1.2 The extended Metropolis sampler

4.1.2.1 Controling the step length

One optionally, as part of running the extended Metropolis sampler, automatically update the 'step'-length of the sequential Gibbs sampler in order to ensure a specific approximate acceptance ratio of the Metropolios sampler. See [CHM12] for details.

The default parameters for adjusting the step length, as given below, are set in the 'prior.seq_gibbs' structure. These parameters will be set the first time 'sippi_prior' is called with the 'prior' structure as output.The default parameters.

```
prior{m}.seq_gibbs.step_min=0;
prior{m}.seq_gibbs.step_min=1;
prior{m}.seq_gibbs.i_update_step=50
prior{m}.seq_gibbs.i_update_step_max=1000
prior{m}.seq_gibbs.n_update_history=50
prior{m}.seq_gibbs.P_target=0.3000
```

By default, adjustment of the step length, in order to achieve an acceptance ratio of 0.3 ('prior{m}.seq_gibbs.P_target'), will be performed for every 50 ('prior{m}.seq_gibbs.i_update_step') iterations, using the acceptance ratio observed in the last 50 ('prior{m}.seq_gibbs.i_update_history') iterations.

Adjustment of the step length will be performed only in the first 1000 ('prior{m}.seq_gibbs.i_update_step_max') iterations.

In order to disable automatiuc adjustment of the step length simply set

```
prior{m}.seq_gibbs.i_update_step_max=0; % disable automatic step length
```

4.1.2.2 The extended independent Metropolis sampler

4.1.2.3 Annealing schedule

4.1.3 linear least squares

4.2 Simulated Annealing

Chapter 5

Examples

SIPPI can be used as a convenient approach for unconditional an conditional simulation.

In ordet to use SIPPI to solve inverse problems, one must provide the solution to the forward problem. Essentially this amounts to implementing a Matlab function that solves the forward problem in using a specific input/output format. If a solution to the forward problem allready exist, this can be quite easily done simply using a Matlab wrapper function.

A few implementations of solutions to forward problems are included as examples as part of SIPPI. These will be demonstrated in the following

5.1 Polynomial line fitting

The forward problem consists of computing the y-value as a function of the x-position of the data, and the polynomial coefficients determining the line. sippi_forward_linefit.m:

```
% sippi_forward_linefit Line fit forward solver for SIPPI
%
% [d,forward,prior,data]=sippi_forward_linefit(m,forward,prior,data);
%
function [d,forward,prior,data]=sippi_forward_linefit(m,forward,prior,data);

if length(m)==1;
    d{1}=forward.x*m{1};
elseif length(m)==2;
    d{1}=forward.x*m{1}+m{2};
else
    d{1}=forward.x.^2*m{1}+forward.x*m{2}+m{3};
end
```

5.2 Covariance model inference

5.3 Cross hole tomography

5.4 Reflection seismic inversion

Chapter 6

Bibliography

[CHM12] K. S. Cordua, T. M. Hansen, and K. Mosegaard, Monte Carlo full waveform inversion of crosshole GPR data using multiple-point geostatistical a priori information, H19--H31.

Geophysics, 77, 2012.

[HCLM13a] T.M. Hansen, K.S. Cordua, M.C. Looms, and K. Mosegaard, SIPPI: a Matlab toolbox for sampling the solution to inverse problems with complex prior information: Part 1, methodology, 470--480.

Computers & Geosciences, 52, 03 2013.

[HCLM13b] T.M. Hansen, K.S. Cordua, M.C. Looms, and K. Mosegaard, SIPPI: a Matlab toolbox for sampling the solution to inverse problems with complex prior information: Part 2, Application to cross hole GPR tomography, 481--492.

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[HCM12] T. M. Hansen, K. C. Cordua, and K. Mosegaard, Inverse problems with non-trivial priors - efficient solution through sequential Gibbs sampling, 593--611.

Computational Geosciences, 16, 2012.

[HCM14] T. M. Hansen, K. S. Cordua, and K. Mosegaard, Accounting for imperfect forward modeling in geophysical inverse problems - exemplified for cross hole tomography, xx.

Accepted for publication in Geophysics, xx, 2014.

Chapter 7

Reference

7.1 SIPPI

7.1.1 getinunits

```
GETINUNITS   Get object properties in specified units
   V = GETINUNITS(H, PROP, UNITS) returns the object property
   in the specified UNITS. It will leave the 'Units' and 'FontUnits'
   property unchanged afterwards.

   H is the handle of the object. If it is an M-element array of handles,
   the function will return an M-by-1 cell array. PROP can be a string or
   a cell array of strings. If it is a 1-by-N or N-by-1 cell array, the
   function will return an M-by-N cell array of values. UNITS can be a
   string or a cell array. If it is a cell array, then PROP must also be a
   cell array with the same size as UNITS, and each cell element of UNITS
   corresponds to a cell element of PROP.

   V = GETINUNITS(H, PROP) is the same as GET(H, PROP)

   Examples:
     V = GETINUNITS(H, 'Position', 'Pixels')
     V = GETINUNITS(H, {'FontSize', 'Position'}, 'Normalized')
     V = GETINUNITS(H, {'FontSize', 'Position'}, {'Points', 'Pixels'})

   See also GET, SET
```

7.1.2 logdet

```
LOGDET Computation of logarithm of determinant of a matrix

   v = logdet(A);
       computes the logarithm of determinant of A.

       Here, A should be a square matrix of double or single class.
       If A is singular, it will returns -inf.

       Theoretically, this function should be functionally
       equivalent to log(det(A)). However, it avoids the
       overflow/underflow problems that are likely to
       happen when applying det to large matrices.
```

```
        The key idea is based on the mathematical fact that
        the determinant of a triangular matrix equals the
        product of its diagonal elements. Hence, the matrix’s
        log-determinant is equal to the sum of their logarithm
        values. By keeping all computations in log-scale, the
        problem of underflow/overflow caused by product of
        many numbers can be effectively circumvented.

        The implementation is based on LU factorization.

    v = logdet(A, ’chol’);
        If A is positive definite, you can tell the function
        to use Cholesky factorization to accomplish the task
        using this syntax, which is substantially more efficient
        for positive definite matrix.

    Remarks
    -------
        logarithm of determinant of a matrix widely occurs in the
        context of multivariate statistics. The log-pdf, entropy,
        and divergence of Gaussian distribution typically comprises
        a term in form of log-determinant. This function might be
        useful there, especially in a high-dimensional space.

        Theoretially, LU, QR can both do the job. However, LU
        factorization is substantially faster. So, for generic
        matrix, LU factorization is adopted.

        For positive definite matrices, such as covariance matrices,
        Cholesky factorization is typically more efficient. And it
        is STRONGLY RECOMMENDED that you use the chol (2nd syntax above)
        when you are sure that you are dealing with a positive definite
        matrix.

    Examples
    --------
        % compute the log-determinant of a generic matrix
        A = rand(1000);
        v = logdet(A);

        % compute the log-determinant of a positive-definite matrix
        A = rand(1000);
        C = A * A’;     % this makes C positive definite
        v = logdet(C, ’chol’);
```

7.1.3 pathdef

```
PATHDEF Search path defaults.
   PATHDEF returns a string that can be used as input to MATLABPATH
   in order to set the path.
```

7.1.4 plotboxpos

```
PLOTBOXPOS Returns the position of the plotted axis region

 pos = plotboxpos(h)
```

```
This function returns the position of the plotted region of an axis,
which may differ from the actual axis position, depending on the axis
limits, data aspect ratio, and plot box aspect ratio.  The position is
returned in the same units as the those used to define the axis itself.
This function can only be used for a 2D plot.

Input variables:

  h:      axis handle of a 2D axis (if ommitted, current axis is used).

Output variables:

  pos:    four-element position vector, in same units as h
```

7.1.5 sippi_adjust_step_size

```
sippi_adjust_step_size Adjust step length length for Metropolis sampler in SIPPI

Call :
  step=sippi_adjust_step_size(step,P_average,P_target);

step : current step
P_current : Current acceptance ratio
P_target  : preferred acceptance ratio (def=0.3);

See also sippi_compute_acceptance_rate, sippi_prior_set_steplength
```

7.1.6 sippi_anneal_adjust_noise

```
sippi_anneal_adjust_noise : Adjust noise level in annealing schedul

Call:
   [data_adjust,mcmc]=sippi_anneal_adjust_noise(data,i,mcmc,prior);

See also: sippi_metropolis, sippi_anneal_factor
```

7.1.7 sippi_anneal_factor

```
sippi_anneal_factor : compute simple noise multiplication factor for
annealing type sampling

See also sippi_metropolis, sippi_anneal_adjust_noise
```

7.1.8 sippi_colormap

```
sippi_colormap Default colormap for sippi

Call :
  sippi_colormap; % the same as sippi_colormap(3);
```

```
or :
  sippi_colormap(1) - Red Green Black
  sippi_colormap(2) - Red Green Blue Black
  sippi_colormap(3) - Jet
```

7.1.9 sippi_compute_acceptance_rate

```
sippi_compute_acceptance_rate Computes acceptance rate for the Metropolis sampler in  ↩
    SIPPI

Call:
  P_acc=sippi_compute_acceptance_rate(acc,n_update_history);
```

7.1.10 sippi_forward

```
sippi_forward Simple forward wrapper for SIPPI

Assumes that the actual forward solver has been defined by
forward.forward_function

Call:
  [d,forward,prior,data]=sippi_forward(m,forward,prior,data,id,im)
```

7.1.11 sippi_forward_traveltime

```
sippi_forward_traveltime Traveltime computation in SIPPI

Call :
  [d,forward,prior,data]=sippi_forward_traveltime(m,forward,prior,data,id,im)

  forward.type determines the method used to compute travel times
  forward.type='ray';
  forward.type='fat';
  forward.type='eikonal';
  forward.type='born';
```

7.1.12 sippi_get_sample

```
sippi_get_sample Get a posterior sample

Call :
 [reals,etype_mean,etype_var]=sippi_get_sample(data,prior,id,im,n_reals,options);
```

7.1.13 sippi_least_squares

```
sippi_least_squares Least squares type inversion for SIPPI

Call :
   [m_reals,m_est,Cm_est]=sippi_least_squares(data,prior,forward,n_reals,lsq_type,id,im);



  lsq_type : 'lsq' (def), classical least squares
             'error_sim', simulation through error simulation
             'visim', simulation through SGSIM of DSSIM
```

7.1.14 sippi_likelihood

```
sippi_likelihood Compute likelihood given an observed dataset

Call
  [logL,L,data]=sippi_likelihood(d,data);


 data{1}.d_obs [N_data,1] N_data data observations
 data{1}.d_std [N_data,1] N_data uncorrelated Gaussian STD

 data{1}.d_var [N_data,1] N_data uncorrelated Gaussian variances


Gaussian modelization error, N(dt,Ct), is specified as
 data{1}.dt [N_data,1] : Bias/mean of modelization error
 data{1}.Ct [N_data,N_data] : Covariance of modelization error

 data{1}.Ct [1,1] : Constant Covariance of modelization error
                    imples data{1}.Ct=ones(N_data.N_data)*data{1}.Ct;




data{id}.recomputeCD [default=0], if '1' then data{1}.iCD is recomputed
each time sippi_likelihood is called. This should be used if the noise model
changes between each call to sippi_likelihood.

 data{id}.full_likelihood [default=]0; if '1' the the full likelihood
 (including the determinant) is computed. This not needed if the data
 civariance is constant, but if it changes, then use
 data{id}.full_likelihood=1;
```

7.1.15 sippi_mcmc_init

```
sippi_mcmc_init Initialize McMC options for Metropolis and rejection sampling in SIPPI

Call:
   options=sippi_mcmc_init(options,prior);
```

7.1.16 sippi_metropolis

```
sippi_metropolis Extended Metropolis sampling in SIPPI

Metropolis sampling.
  See e.g. Hansen, T. M., Cordua, K. S., and Mosegaard, K., 2012.
    Inverse problems with non-trivial priors - Efficient solution through Sequential ↩
        Gibbs Sampling.
    Computational Geosciences. doi:10.1007/s10596-011-9271-1.

Call :
   [options,data,prior,forward,m_current]=sippi_metropolis(data,prior,forward,options)
Input :
   data : sippi data structure
   prior : sippi prior structure
   forward : sippi forward structure

options :
   options.txt [string] : string to be used as part of all output files

   options.mcmc.nite [1]  : Number if iterations
   options.mcmc.i_plot [1]: Number of iterations between updating plots
   options.mcmc.i_sample=: Number of iterations between saving model to disk

   options.mcmc.m_init : Manually chosen starting model
   options.mcmc.m_ref  : Reference known target model

   options_mcmc.accept_only_improvements [0] : Optimization

  %% PERTUBATION STRATEGY
  options.mcmc.pert_strategy.perturb_all=1; % Perturb all priors in each
                                            % iteration. def =[0]
   %% SIMULATED ANNEALING
   options.mcmc.anneal.i_begin=1; % default, iteration number when annealing begins
   options.mcmc.anneal.i_end=100000; %  iteration number when annealing stops
   options.mcmc.anneal.fac_begin=20; % default, noise is scaled by fac_begin at iteration ↩
        i_begin
   options.mcmc.anneal.fac_end=1; % default, noise is scaled by fac_end at iteration  ↩
       i_end


See also sippi_rejection
```

7.1.17 sippi_plot_current_model

```
sippi_plot_current_model Plots the current model during Metropolis sampling

Call :
  sippi_plot_current_model(mcmc,data,d,m_current,prior);
```

7.1.18 sippi_plot_data

```
sippi_plot_data plot data in SIPPI

Call.
   sippi_plot_data(d,data);
```

```
```

7.1.19 sippi_plot_loglikelihood

```
sippi_plot_loglikelihood Plot loglikelihood time series

Call :
   acc=sippi_plot_loglikelihood(logL,i_acc,N,itext)
```

7.1.20 sippi_plot_model

```
sippi_plot_model Plot a 'model', i.e. a realization of the prior model


Call :
  sippi_plot_model(prior,m,im_array);

  prior : Matlab structure for SIPPI prior model
  m : Matlab structure for SIPPI realization
  im_array : integer array of type of models to plot (typically 1)


Example
  m=sippi_prior(prior);
  sippi_plot_model(prior,m);

  m=sippi_prior(prior);
  sippi_plot_model(prior,m,2);

See also sippi_plot_prior
```

7.1.21 sippi_plot_movie

```
sippi_plot_movie plot movie of prior and posterior realizations

Call :
  sippi_plot_movie(fname);
  sippi_plot_movie(fname,im_array,n_frames,skip_burnin);
     fname : name of folder with results (e.g. options.txt)
     im_array : array of indexes of model parameters to make into movies
     n_frames [200] : number of frames in movie
     skip_burnin [200] : start movie after burn_in;

Ex:
sippi_plot_movie('20130812_Metropolis');
sippi_plot_movie(options.txt);

%% 1000 realization including burn-in, for prior number 1
sippi_plot_movie('20130812_Metropolis',1,1000,0);
```

7.1.22 sippi_plot_posterior

```
sippi_plot_posterior Plot statistics from posterior sample

Call :
   sippi_plot_posterior(fname,im_arr,prior,options,n_reals);

See also sippi_plot_prior
```

7.1.23 sippi_plot_prior

```
sippi_plot_prior Plot a sample of the prior in SIPPI

Call :
   sippi_plot_prior(prior,ip,n_reals,cax,supt);

 See also sippi_plot_posterior, sippi_plot_model
```

7.1.24 sippi_prior

```
 sippi_prior A priori models for SIPPI

 To generate a realization of the prior model defined by the prior structure use:
   [m_propose,prior]=sippi_prior(prior);

 To generate a realization of the prior model defined by the prior structure,
 in the vicinity of a current model (using sequential Gibbs sampling) use:
   [m_propose,prior]=sippi_prior(prior,m_current);

 The following types of a priori models can be used
   SNESIM  [1D-3D] : based on a multiple point statistical model inferref from a training ↩
       images. Relies in the SNESIM algorithm
   SISIM   [1D-3D] : based on Sequential indicator SIMULATION
   VISIM   [1D-3D] : based on Sequential Gaussian and Direct Sequential simulation
   FFTMA   [1D-3D] : based on the FFT-MA method (Multivariate Gaussian)
   GAUSSIAN   [1D] : 1D generalized gaussian model


%%% SIMPLE EXAMPLE %%%

% A simple 2D multivariate Gaissian based prior model based on the
% FFT-MA method, can be defined using
   im=1;
   prior{im}.type='FFTMA';
   prior{im}.name='A SIMPLE PRIOR';
   prior{im}.x=[0:1:100];
   prior{im}.y=[0:1:100];
   prior{im}.m0=10;
   prior{im}.Va='1 Sph(10)';
   prior=sippi_prior_init(prior);
% A realization from this prior model can be generated using
   m=sippi_prior(prior);
% This realization can now be plotted using
   sippi_plot_prior(m,prior);
% or
   imagesc(prior{1}.x,prior{1}.y,m{1})
```

```
%%% A PRIOR MODEL WITH SEVERAL 'TYPES OF A PRIORI MODEL'

   im=1;
   prior{im}.type='GAUSSIAN';
   prior{im}.m0=100;
   prior{im}.std=50;
   prior{im}.norm=100;
   im=2;
   prior{im}.type='FFTMA';
   prior{im}.x=[0:1:100];
   prior{im}.y=[0:1:100];
   prior{im}.m0=10;
   prior{im}.Cm='1 Sph(10)';
   im=3;
   prior{im}.type='SISIM';
   prior{im}.x=[0:1:100];
   prior{im}.y=[0:1:100];
   prior{im}.m0=10;
   prior{im}.Cm='1 Sph(10)';
   im=4;
   prior{im}.type='SNESIM';
   prior{im}.x=[0:1:100];
   prior{im}.y=[0:1:100];

   sippi_plot_model(prior);

%% Sequential Gibbs sampling

   All a priori model types can be perturbed, such that a new realization
   is generated in the vicinity of a current model.
   To do this Sequential Gibbs Sampling is used.
   For more information, see <a href="matlab:web('http://dx.doi.org/10.1007/s10596 ↩
       -011-9271-1')">Hansen, T. M., Cordua, K. S., and Mosegaard, K., 2012. Inverse  ↩
       problems with non-trivial priors - Efficient solution through Sequential Gibbs  ↩
       Sampling. Computational Geosciences</a>.
   The type of sequential Gibbs sampling can be controlled in the
   'seq_gibbs' structures, e.g. prior{1}.seq_gibbs

   im=1;
   prior{im}.type='SNESIM';
   prior{im}.x=[0:1:100];
   prior{im}.y=[0:1:100];

   [m,prior]=sippi_prior(prior);
   prior{1}.seq_gibbs.step=1; % Large step--> independant realizations
   prior{1}.seq_gibbs.step=.1; % Smaller step--> Dependant realizations
   for i=1:30;
      [m,prior]=sippi_prior(prior,m); % One iteration of Sequential Gibbs
      sippi_plot_model(prior,m);
   end

 See also: sippi_prior_init, sippi_plot_prior, sippi_prior_set_steplength.m

 TMH/2012
```

7.1.25 sippi_prior_fftma

```
 sippi_prior A priori models for SIPPI
 To generate a realization of the prior model defined by the prior structure use:
   [m_propose,prior]=sippi_prior(prior);

 To generate a realization of the prior model defined by the prior structure,
 in the vicinity of a current model (using sequential Gibbs sampling) use:
   [m_propose,prior]=sippi_prior(prior,m_current);

 The following types of a priori models can be used
   SNESIM  [1D-3D] : based on a multiple point statistical model inferref from a training ↩
       images. Relies in the SNESIM algorithm
   SISIM   [1D-3D] : based on Sequential indicator SIMULATION
   VISIM   [1D-3D] : based on Sequential Gaussian and Direct Sequential simulation
   FFTMA   [1D-3D] : based on the FFT-MA method (Multivariate Gaussian)
   GAUSSIAN   [1D] : 1D generalized gaussian model


%%% SIMPLE EXAMPLE %%%

% A simple 2D multivariate Gaissian based prior model based on the
% FFT-MA method, can be defined using
   id=1;
   prior{id}.type='FFTMA';
   prior{id}.name='A SIMPLE PRIOR';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Va='1 Sph(10)';
   prior=sippi_prior_init(prior);
% A realization from this prior model can be generated using
   m=sippi_prior(prior);
% This realization can now be plotted using
   sippi_plot_prior(m,prior);
% or
   imagesc(prior{1}.x,prior{1}.y,m{1})

%%% A PRIOR MODEL WITH SEVERAL 'TYPES OF A PRIORI MODEL'

   id=1;
   prior{id}.type='FFTMA';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Cm='1 Sph(10)';
   id=2;
   prior{id}.type='SISIM';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Cm='1 Sph(10)';
   id=3;
   prior{id}.type='GAUSSIAN';
   prior{id}.m0=100;
   prior{id}.std=50;
   prior{id}.norm=100;
   prior=sippi_prior_init(prior);

   sippi_plot_model(prior);

%% Sequential Gibbs sampling
% For more information, see <a href="matlab:web('http://dx.doi.org/10.1007/s10596 ↩
    -011-9271-1')">Hansen, T. M., Cordua, K. S., and Mosegaard, K., 2012. Inverse problems ↩
    with non-trivial priors - Efficient solution through Sequential Gibbs Sampling.  ↩
    Computational Geosciences</a>.


 See also: sippi_prior_init, sippi_plot_prior, sippi_prior_set_steplength.m

 TMH/2012
```

7.1.26 sippi_prior_init

```
 sippi_prior_init Initialize PRIOR structure for SIPPI

 Call
   prior=sippi_prior_init(prior);

 See also sippi_prior
```

7.1.27 sippi_prior_new

```
 sippi_prior A priori models for SIPPI

 To generate a realization of the prior model defined by the prior structure use:
   [m_propose,prior]=sippi_prior(prior);

 To generate a realization of the prior model defined by the prior structure,
 in the vicinity of a current model (using sequential Gibbs sampling) use:
   [m_propose,prior]=sippi_prior(prior,m_current);

 The following types of a priori models can be used
   SNESIM  [1D-3D] : based on a multiple point statistical model inferref from a training  ↩
       images. Relies in the SNESIM algorithm
   SISIM   [1D-3D] : based on Sequential indicator SIMULATION
   VISIM   [1D-3D] : based on Sequential Gaussian and Direct Sequential simulation
   FFTMA   [1D-3D] : based on the FFT-MA method (Multivariate Gaussian)
   GAUSSIAN   [1D] : 1D generalized gaussian model


%%% SIMPLE EXAMPLE %%%

% A simple 2D multivariate Gaissian based prior model based on the
% FFT-MA method, can be defined using
   id=1;
   prior{id}.type='FFTMA';
   prior{id}.name='A SIMPLE PRIOR';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Va='1 Sph(10)';
   prior=sippi_prior_init(prior);
% A realization from this prior model can be generated using
   m=sippi_prior(prior);
% This realization can now be plotted using
   sippi_plot_prior(m,prior);
% or
   imagesc(prior{1}.x,prior{1}.y,m{1})
```

```
%%% A PRIOR MODEL WITH SEVERAL 'TYPES OF A PRIORI MODEL'

   id=1;
   prior{id}.type='FFTMA';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Cm='1 Sph(10)';
   id=2;
   prior{id}.type='SISIM';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Cm='1 Sph(10)';
   id=3;
   prior{id}.type='GAUSSIAN';
   prior{id}.m0=100;
   prior{id}.std=50;
   prior{id}.norm=100;
   prior=sippi_prior_init(prior);

   sippi_plot_model(prior);

%% Sequential Gibbs sampling
% For more information, see <a href="matlab:web('http://dx.doi.org/10.1007/s10596 ↩
    -011-9271-1')">Hansen, T. M., Cordua, K. S., and Mosegaard, K., 2012. Inverse problems  ↩
    with non-trivial priors - Efficient solution through Sequential Gibbs Sampling.  ↩
    Computational Geosciences</a>.


 See also: sippi_prior_init, sippi_plot_prior, sippi_prior_set_steplength.m

 TMH/2012
```

7.1.28 sippi_prior_old

```
 sippi_prior A priori models for SIPPI

 To generate a realization of the prior model defined by the prior structure use:
   [m_propose,prior]=sippi_prior(prior);

 To generate a realization of the prior model defined by the prior structure,
 in the vicinity of a current model (using sequential Gibbs sampling) use:
   [m_propose,prior]=sippi_prior(prior,m_current);

 The following types of a priori models can be used
   SNESIM  [1D-3D] : based on a multiple point statistical model inferref from a training  ↩
       images. Relies in the SNESIM algorithm
   SISIM   [1D-3D] : based on Sequential indicator SIMULATION
   VISIM   [1D-3D] : based on Sequential Gaussian and Direct Sequential simulation
   FFTMA   [1D-3D] : based on the FFT-MA method (Multivariate Gaussian)
   GAUSSIAN   [1D] : 1D generalized gaussian model


%%% SIMPLE EXAMPLE %%%

% A simple 2D multivariate Gaissian based prior model based on the
% FFT-MA method, can be defined using
   id=1;
   prior{id}.type='FFTMA';
   prior{id}.name='A SIMPLE PRIOR';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Va='1 Sph(10)';
   prior=sippi_prior_init(prior);
% A realization from this prior model can be generated using
   m=sippi_prior(prior);
% This realization can now be plotted using
   sippi_plot_prior(m,prior);
% or
   imagesc(prior{1}.x,prior{1}.y,m{1})

%%% A PRIOR MODEL WITH SEVERAL 'TYPES OF A PRIORI MODEL'

   id=1;
   prior{id}.type='FFTMA';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Cm='1 Sph(10)';
   id=2;
   prior{id}.type='SISIM';
   prior{id}.x=[0:1:100];
   prior{id}.y=[0:1:100];
   prior{id}.m0=10;
   prior{id}.Cm='1 Sph(10)';
   id=3;
   prior{id}.type='GAUSSIAN';
   prior{id}.m0=100;
   prior{id}.std=50;
   prior{id}.norm=100;
   prior=sippi_prior_init(prior);

   sippi_plot_model(prior);

%% Sequential Gibbs sampling
% For more information, see <a href="matlab:web('http://dx.doi.org/10.1007/s10596 ↩
   -011-9271-1')">Hansen, T. M., Cordua, K. S., and Mosegaard, K., 2012. Inverse problems ↩
    with non-trivial priors - Efficient solution through Sequential Gibbs Sampling. ↩
    Computational Geosciences</a>.


 See also: sippi_prior_init, sippi_plot_prior, sippi_prior_set_steplength.m

 TMH/2012
```

7.1.29 sippi_prior_set_steplength

```
 sippi_prior_set_steplength Set step length for Metropolis sampler in SIPPI

 Call
   prior=sippi_prior_set_steplength(prior,mcmc,im);
```

7.1.30 sippi_rejection

```
sippi_rejection Rejection sampling

Call :
    options=sippi_rejection(data,prior,forward,options)

input arguments

  options.mcmc.i_plot
  options.mcmc.nite     % maximum number of iterations
  options.mcmc.logLmax

  options.mcmc.rejection_normalize_log = log(options.mcmc.Lmax)

  options.mcmc.adaptive_rejection=1, adaptive setting of maxiumum likelihood
               (def=[0])
               At each iteration Lmax will be set if log(L(m_cur)=>options.mcmc.logLmax


  options.mcmc.max_run_time_hours = 1; % maximum runtime in hours
                                       % (overrides options.mcmc.nite if needed)

See also sippi_metropolis
```

7.1.31 sippi_set_path

```
sippi_set_path Set paths for running sippi
```

7.2 SIPPI toolbox: Traveltime tomography

7.2.1 calc_Cd

```
Calc_cd Setup a covariance model to account for borehole imperfections

Call: Cd=calc_Cd(ant_pos,var_uncor,var_cor1,var_cor2,L)
This function sets up a data covariance matrix that accounts for static
(i.e. correlated) data errors.

Inputs:
* ant_pos: A N x 4 array that contains N combinations of transmitter/source
and receiver positions. The first two columns are the x- and y-coordinates
of the transmitter/source position. The last two columns are the x- and
y-coordiantes of the receiver position.
* var_uncor: The variance of the uncorrelated data errors.
* var_cor1: The variance of the correlated data errors
related to the transmitter/source positions.
* var_cor2: The variance of the correlated data errors
related to the receiver positions.
* L: The correlation length for the correlation between the individual
transmitter/source or receiver positions using an exponential covariance
function. For typical static errors the correlation length is set to a
small number (e.g. 10^-6).

For more details and practical examples see:
Cordua et al., 2008 in Vadose zone journal.
Cordua et al., 2009 in Journal of applied geophysics.

Knud S. Cordua (2012)
```

7.2.2 eikonal

```
eikonal Traveltime computation by solving the eikonal equation

tmap=eikonal(x,y,z,V,Sources,type);

 x,y,z : arrays defining the x, y, and z axis
 V: velocity field, with size (length(y),length(x),length(z));
 Sources [ndata,ndim] : Source positions
 type (optional): type of eikonal solver: [1]:Fast Marching(default), [2]:FD

 tmap [size(V)]: travel times computed everywhere in the velocity grid

%Example (2D):
  x=[1:1:100];
  y=1:1:100;
  z=1;
  V=ones(100,100);V(:,1:50)=2;
  Sources = [10 50;75 50];
  t=eikonal(x,y,z,V,Sources);
  subplot(1,2,1);imagesc(x,y,t(:,:,1,1));axis image;colorbar
  subplot(1,2,2);imagesc(x,y,t(:,:,1,2));axis image;colorbar

See also eikonal_traveltime
```

7.2.3 eikonal_raylength

```
eikonal_raylength : Computes the raylength from S to R using the eikonal equaiton

Call:
  raylength=eikonal_raylength(x,y,v,S,R,tS,doPlot)
```

7.2.4 eikonal_traveltime

```
eikonal_traveltime Computes traveltime between sources and receivers by solving the ↩
    eikonal equation

t=eikonal_traveltime(x,y,z,V,Sources,Receivers,iuse,type);

 x,y,z : arrays defining the x, y, and z axis
 V: velocity field, with size (length(y),length(x),length(z));
 Sources [ndata,ndim] : Source positions
 Receivers [ndata,ndim] : Receiver positions
 iuse (optional): optionally only use subset of data. eg.g i_use=[1 2 4];
 type (optional): type of eikonal solver: [1]:Fast Marching(default), [2]:FD

 tmap [size(V)]: travel times computed everywhere in the velocity grid

%Example (2%
Example 2d traveltime compuation

Example (2D):
  x=[1:1:100];
  y=1:1:100;
  z=1;
  V=ones(100,100);V(:,1:50)=2;
  S=[50 50 1;50 50 1];
  R=[90 90 1; 90 80 1];
  t=eikonal_traveltime(x,y,z,V,S,R)

Example (3D):
  nx=50;ny=50;nz=50;
  x=1:1:nx;
  y=1:1:ny;
  z=1:1:nz;
  V=ones(ny,nx,nz);V(:,1:50,:)=2;
  S=[10 10 1;10 10 1;10 9 1];
  R=[40 40 40; 40 39 40; 40 40 40];
  t=eikonal_traveltime(x,y,z,V,S,R)


See also eikonal
```

7.2.5 kernel_buursink_2d

```
kernel_buursink_2k Computes 2D Sensitivity kernel based on 1st order EM scattering theory

See
  Buursink et al. 2008. Crosshole radar velocity tomography
                        with finite-frequency Fresnel. Geophys J. Int.
                        (172) 117;

 CALL :
    % specify a source trace (dt, wf_trace):
    [kernel,L,L1_all,L2_all]=kernel_buursink_2d(model,x,z,S,R,dt,wf_trace);
    % Use a ricker wavelet with center frequency 'f0'
    [kernel,L,L1_all,L2_all]=kernel_buursink_2d(model,x,z,S,R,f0));


Knud Cordua, 2009,
Thomas Mejer Hansen (small edits, 2009)
```

7.2.6 kernel_finite_2d

```
kernel_finite_2d 2D sensitivity kernels

 Call:
   [Knorm,K,dt,options]=kernel_finite_2d(v_ref,x,y,S,R,freq,options);
```

7.2.7 kernel_fresnel_2d

```
kernel_fresnel_2d Sensitivity kernel for amplitude and first arrival

Call:
  [kernel_t,kernel_a,P_omega,omega]=kernel_fresnel_2d(v,x,y,S,R,omega,P_omega);


Based on Liu, Dong, Wang, Zhu and Ma, 2009, Sensitivity kernels for
seismic Fresenl volume Tomography, Geophysics, 75(5), U35-U46

See also kernel_fresnel_monochrome_2d

Run with no argument for an example.
```

7.2.8 kernel_fresnel_monochrome_2d

```
kernel_fresnel_monochrome_2d 2D monchrome kernel for amplitude and first arrival

Call:
  [kernel_t,kernel_a]=kernel_fresnel_monochrome_2d(v,x,y,S,R,omega);
or
  [kernel_t,kernel_a]=kernel_fresnel_monochrome_2d(v,x,y,S,R,omega,L,L1,L2);

Based on Liu, Dong, Wang, Zhu and Ma, 2009, Sensitivity kernels for
seismic Fresenl volume Tomography, Geophysics, 75(5), U35-U46

See also, kernel_fresnel_2d
```

7.2.9 kernel_multiple

```
kernel_multiple Computes the sensitivity kernel for a wave traveling
from S to R.

CALL :
   [K,RAY,Gk,Gray,timeS,timeR,raypath]=kernel_multiple(Vel,x,y,z,S,R,T,alpha,Knorm);

IN :
   Vel [ny,nx] : Velocity field
   x [1:nx] :
   y [1:ny] :
   z [1:nz] :
   S [1,3] : Location of Source
   R [1,3] : Location of Receiver
   T : Donminant period
   alpha: controls exponential decay away ray path
   Knorm [1] : normaliztion of K [0]:none, K:[1]:vertical

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

The sensitivity is the length travelled in each cell.


See also : fast_fd_2d
```

```
TMH/2006
```

7.2.10 kernel_slowness_to_velocity

```
kernel_slowness_to_velocity Converts from slowness to velocity parameterizations

G : kernel [1,nkernels]
V : Velocity field (


CALL:
  G_vel=kernel_slowness_to_velocity(G,V);
or
  [G_vel,v_obs]=kernel_slowness_to_velocity(G,V,t);
or
  [G_vel,v_obs,Cd_v]=kernel_slowness_to_velocity(G,V,t,Cd);
```

7.2.11 mspectrum

```
mspectrum : Amplitude and Power spectrum
Call   :
    function [A,P,smoothP,kx]=mspectrum(x,dx)

1D (A)mplitude and (P)owerspectrum of x-series with spacing dx
```

7.2.12 munk_fresnel_2d

```
2D frechet kernel, First Fresnel Zone

See Jensen, Jacobsen, Christensen-Dalsgaard (2000) Solar Physics 192.

Call :
S=munk_fresnel_2d(T,dt,alpha,As,Ar,K);

T : dominant period
dt :
alpha : degree of cancellation
As : Amplitude fo the wavefield propagating from the source
Ar : Amplitude fo the wavefield propagating from the receiver
K : normalization factor
```

7.2.13 munk_fresnel_3d

```
3D frechet kernel, First Fresnel Zone

See Jensen, Jacobsen, Christensen-Dalsgaard (2000) Solar Physics 192.

Call :
```

7.2.14 tomography_kernel

```
tomography_kernel Computes the sensitivity kernel for a wave traveling from S to R.

CALL :
   [K,RAY,Gk,Gray,timeS,timeR,raypath]=tomography_kernel(Vel,x,y,z,S,R,T,alpha,Knorm);

IN :
   Vel [ny,nx] : Velocity field
   x [1:nx] :
   y [1:ny] :
   z [1:nz] :
   S [1,3] : Location of Source
   R [1,3] : Location of Receiver
   T : Donminant period
   alpha: controls exponential decay away ray path
   Knorm [1] : normaliztion of K [0]:none, K:[1]:vertical

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

The sensitivity is the length travelled in each cell.
```