

# Package ‘gasper’

February 11, 2023

**Type** Package

**Title** Graph Signal Processing

**Version** 1.1.3

**Description** Provides the standard operations for signal processing on graphs: graph Fourier transform, spectral graph wavelet transform, visualization tools. It also implements a data driven method for graph signal denoising/regression, for details see De Loynes, Navarro, Olivier (2019) <[arxiv:1906.01882](https://arxiv.org/abs/1906.01882)>. The package also provides an interface to the SuiteSparse Matrix Collection, <<https://sparse.tamu.edu/>>, a large and widely used set of sparse matrix benchmarks collected from a wide range of applications.

**URL** <https://github.com/fabnavarro/gasper>

**BugReports** <https://github.com/fabnavarro/gasper/issues>

**License** LGPL (>= 2)

**Encoding** UTF-8

**LazyData** true

**RoxygenNote** 7.2.3

**Imports** Rcpp, ggplot2, methods, Matrix, RSpectra, httr, curl

**LinkingTo** Rcpp, RcppArmadillo

**Suggests** knitr, rmarkdown

**VignetteBuilder** knitr

**NeedsCompilation** yes

**Author** Fabien Navarro [aut, cre],  
Basile de Loynes [aut],  
Baptiste Olivier [aut]

**Maintainer** Fabien Navarro <[fabien.navarro@math.cnrs.fr](mailto:fabien.navarro@math.cnrs.fr)>

**Repository** CRAN

**Date/Publication** 2023-02-11 16:10:02 UTC

**R topics documented:**

adjacency_mat . . . . .	2
analysis . . . . .	3
betathresh . . . . .	4
download_graph . . . . .	4
eigendec . . . . .	5
eigensort . . . . .	5
forward_sgw . . . . .	6
full . . . . .	7
fullup . . . . .	7
grid1 . . . . .	8
GVN . . . . .	8
HPFVN . . . . .	9
inverse_sgw . . . . .	10
laplacian_mat . . . . .	11
matmult . . . . .	11
minnesota . . . . .	12
NYCdata . . . . .	12
pittsburgh . . . . .	13
plot_filter . . . . .	13
plot_graph . . . . .	14
plot_signal . . . . .	14
PSNR . . . . .	15
randsignal . . . . .	16
rlogo . . . . .	16
smoothmodulus . . . . .	17
SNR . . . . .	17
SUREthresh . . . . .	18
SURE_MSEthresh . . . . .	19
swissroll . . . . .	20
synthesis . . . . .	21
tight_frame . . . . .	21
zetav . . . . .	22
<b>Index</b>	<b>23</b>

---

adjacency\_mat

*Compute the adjacency matrix of the gaussian weighted graph*


---

**Description**

Compute the adjacency matrix of the gaussian weighted graph

**Usage**

```
adjacency_mat(  
  pts,  
  f = function(x) {  
    exp(-x^2/8)  
  },  
  s = 0  
)
```

**Arguments**

pts	coordinates of N points in $R^3$ .
f	is a scalar potential ( $\exp(-x^2/2t^2)$ for gaussian potential)
s	is a threshold to sparify the matrix

**See Also**

[laplacian\\_mat](#), [swissroll](#)

**Examples**

```
pts <- swissroll(N=100, seed=0, a=1, b=4)  
W <- adjacency_mat(pts)
```

---

analysis

*Analysis operator.*

---

**Description**

Compute the analysis operator for coefficient y.

**Usage**

```
analysis(y, tf)
```

**Arguments**

y	Graph signal to analyze.
tf	frame coefficients.

**Value**

coef Transform coefficients.

**See Also**

[synthesis](#), [tight\\_frame](#)

---

betathresh	<i>Apply Beta Threshold.</i>
------------	------------------------------

---

**Description**

Apply Beta Threshold.

**Usage**

```
betathresh(y, t, b)
```

**Arguments**

y	Noisy Data.
t	Threshold.
b	Thresholding type (b=1: soft, b=2: JS).

**Value**

x Filtered result.

---

download_graph	<i>Download sparse matrix form the SuiteSparse Matrix Collection.</i>
----------------	---

---

**Description**

If coordinates are associated with the graphs, they are automatically downloaded and added to the output. See <https://sparse.tamu.edu/> for the list of groups and graph names.

**Usage**

```
download_graph(matrixname, groupname)
```

**Arguments**

matrixname	Name of the graph to download.
groupname	Name of the group that provides the graph.

**Value**

matrixname a list contening the sparse matrix *sA*, *xy* coordinates (if any), *dim* the number of rows, columns and numerically nonzero elements and *info*, the path to a plain txt file containing information associated with *sA* (accessible for example via `file.show(matrixname$info)`).

## References

Davis, T. A., & Hu, Y. (2011). The University of Florida sparse matrix collection. *ACM Transactions on Mathematical Software (TOMS)*, 38(1), 1-25.

## Examples

```
matrixname <- "grid1"
groupname <- "AG-Monien"
download_graph(matrixname,groupname)
file.show(grid1$info)
```

---

eigendec	<i>Spectral decomposition of a symmetric matrix</i>
----------	---

---

## Description

Eigen decomposition of dense symmetric/hermitian matrix M using divide-and-conquer methods that provides slightly different results than the standard method, but is considerably faster for large matrices.

## Usage

```
eigendec(M)
```

## Arguments

M	a matrix.
---	-----------

---

eigensort	<i>Spectral decomposition of a symmetric matrix.</i>
-----------	--

---

## Description

Computes eigenvalues and eigenvectors of matrices (output sorted in increasing order).

## Usage

```
eigensort(x)
```

## Arguments

x	Symmetric matrix (sparse or dense) whose spectral decomposition is to be computed.
---	--

## Examples

```
A <- matrix(1, ncol=2, nrow=2)
dec <- eigensort(A)
```

---

`forward_sgw`*Compute Forward Spectral Graph Wavelet Transform.*

---

**Description**

Compute forward SGWT for signal  $f$  (without frame calculation). The calculation corresponds to the frame defined by the ‘tight\_frame’ function (without explicit calculation of the latter).

**Usage**

```
forward_sgw(f, values, vectors, b = 2)
```

**Arguments**

<code>f</code>	Graph signal to analyze.
<code>values</code>	Eigenvalues of the Laplacian matrix.
<code>vectors</code>	Eigenvectors of the Laplacian matrix.
<code>b</code>	Parameter that control the number of scales.

**Value**

wc wavelet coefficients.

**References**

Göbel, F., Blanchard, G., von Luxburg, U. (2018). Construction of tight frames on graphs and application to denoising. In Handbook of Big Data Analytics (pp. 503-522). Springer, Cham.

de Loynes, B., Navarro, F., Olivier, B. (2021). Data-driven thresholding in denoising with Spectral Graph Wavelet Transform. Journal of Computational and Applied Mathematics, Vol. 389.

Hammond, D. K., Vandergheynst, P., & Gribonval, R. (2011). Wavelets on graphs via spectral graph theory. Applied and Computational Harmonic Analysis, 30(2), 129-150.

**See Also**

[inverse\\_sgw](#), [tight\\_frame](#)

---

full	<i>Convert symmetric sparse matrix to full matrix.</i>
------	--

---

**Description**

Convert a symmetric sparse matrix sA to full matrix A.

**Usage**

```
full(sA)
```

**Arguments**

sA                    Sparse matrix to convert.

**See Also**

[fullup](#)

[fullup](#)

**Examples**

```
sA <- pittsburgh$sA  
A <- full(sA)
```

---

fullup	<i>Convert symmetric sparse matrix to full matrix.</i>
--------	--

---

**Description**

Convert a symmetric sparse matrix sA stored as upper triangular matrix to full matrix A.

**Usage**

```
fullup(sA)
```

**Arguments**

sA                    Sparse upper triangular matrix to convert.

**See Also**

[full](#)

**Examples**

```
data(grid1)  
A <- fullup(grid1$sA)
```

---

grid1	<i>grid1 graph.</i>
-------	---------------------

---

**Description**

A dataset containing grid1 graph.

**Usage**

grid1

**Format**

list of 2 elements

xy coordinates

sA adjacency matrix

---

GVN	<i>Graph Von Neumann Estimator.</i>
-----	-------------------------------------

---

**Description**

Graph equivalent of the Von Neumann variance estimator.

**Usage**

GVN(y, A, L)

**Arguments**

y Noisy data.

A Adjacency matrix.

L Laplacian matrix.

**References**

von Neumann, J. (1941). Distribution of the ratio of the mean square successive difference to the variance. *Ann. Math. Statistics*, 35(3), 433–451.

de Loynes, B., Navarro, F., Olivier, B. (2021). Data-driven thresholding in denoising with Spectral Graph Wavelet Transform. *Journal of Computational and Applied Mathematics*, Vol. 389.

**See Also**

[HPFVN](#)



**Examples**

```
data(minnesota)
A <- minnesota$A
L <- laplacian_mat(A)
x <- minnesota$xy[,1]
n <- length(x)
f <- sin(x)
sigma <- 0.1
noise <- rnorm(n, sd = sigma)
y <- f + noise
sigma^2
GVN(y, A, L)
```

---

HPFVN

*High Pass Filter Von Neumann Estimator.*

---

**Description**

Graph extension of the Von Neumann variance estimator using finest scale coefficients.

**Usage**

```
HPFVN(wcn, evalues, b)
```

**Arguments**

wcn	Noisy wavelet coefficients.
evalues	Laplacian spectrum.
b	Parameter that control the number of scales.

**References**

von Neumann, J. (1941). Distribution of the ratio of the mean square successive difference to the variance. *Ann. Math. Statistics*, 35(3), 433–451.

de Loynes, B., Navarro, F., Olivier, B. (2021). Data-driven thresholding in denoising with Spectral Graph Wavelet Transform. *Journal of Computational and Applied Mathematics*, Vol. 389.

**See Also**

[GVN](#)

**Examples**

```

data(grid1)
A <- grid1$sA
L <- laplacian_mat(A)
x <- grid1$xy[,1]
n <- length(x)
val1 <- eigensort(L)
evalues <- val1$evalues
eectors <- val1$eectors
f <- sin(x)
sigma <- 0.1
noise <- rnorm(n, sd = sigma)
y <- f + noise
b <- 2
wcn <- forward_sgwt(y, evalues, eectors, b=b)
sigma^2
HPFVN(wcn, evalues, b)

```

---

inverse\_sgwt

---

*Compute Inverse Spectral Graph Wavelet Transform.*


---

**Description**

Compute inverse (adjoint) SGWT for signal  $f$  (without frame calculation). The calculation is performed for the frame defined by the ‘tight\_frame’ function. The tightness of the underlying frame implies that the computation is obtained by simply applying the adjoint linear transformation to the wavelet coefficients.

**Usage**

```
inverse_sgwt(wc, evalues, eectors, b = 2)
```

**Arguments**

wc	Wavelet coefficients.
evalues	Eigenvalues of the Laplacian matrix.
eectors	Eigenvectors of the Laplacian matrix.
b	Parameter that control the number of scales.

**Value**

$f$  SGWT adjoint applied to  $wc$ .

**References**

- Göbel, F., Blanchard, G., von Luxburg, U. (2018). Construction of tight frames on graphs and application to denoising. In Handbook of Big Data Analytics (pp. 503-522). Springer, Cham.
- de Loynes, B., Navarro, F., Olivier, B. (2021). Data-driven thresholding in denoising with Spectral Graph Wavelet Transform. Journal of Computational and Applied Mathematics, Vol. 389.
- Hammond, D. K., Vandergheynst, P., & Gribonval, R. (2011). Wavelets on graphs via spectral graph theory. Applied and Computational Harmonic Analysis, 30(2), 129-150.

**See Also**

[forward\\_sgwt](#), [tight\\_frame](#)

---

laplacian_mat	<i>Laplacian matrix.</i>
---------------	--------------------------

---

**Description**

Compute the (unnormalized) laplacian matrix from the adjacency matrix.

**Usage**

```
laplacian_mat(W)
```

**Arguments**

W                      Adjacency matrix.

**Value**

L (unnormalized) Laplacian matrix.

---

matmult	<i>Matrix multiplication</i>
---------	------------------------------

---

**Description**

Matrix multiplication

**Usage**

```
matmult(A, B)
```

**Arguments**

A                      a matrix.  
B                      a matrix.

---

minnesota

*Minnesota road network.*

---

### Description

A dataset containing the minnesota road network (as well as the two signals).

### Usage

minnesota

### Format

list of 6 elements

**xy** coordinates

**A** adjacency matrix

**sA** sparse version of A

**f1**  $\eta=0.01$  and  $k=2$

**f2**  $\eta = 0.001$  and  $k=4$

**labels** labels

### Source

D. Gleich. The MatlabBGL Matlab library. [https://www.cs.purdue.edu/homes/dgleich/packages/matlab\\_bgl/index.html](https://www.cs.purdue.edu/homes/dgleich/packages/matlab_bgl/index.html).

---

NYCdata

*NYC network.*

---

### Description

A dataset containing the NYC network.

### Usage

NYCdata

### Format

list of 2 elements

**A** NYC adjacency matrix (built using exponential weights between two nodes).

**f** median price observed from miles travelled to the given drop off point.

---

pittsburgh                      *Pittsburgh network.*

---

### Description

A dataset containing the pittsburgh network.

### Usage

pittsburgh

### Format

list of 7 elements

**A** pittsburgh adjacency matrix

**sA** pittsburgh sparse adjacency matrix

**xy** coordinates

**f** signal used in Trend filtering on graphs

**y** noisy signal used in Trend filtering on graph

**f1**  $\eta=0.01, k=5$

**geo** geometry

### Source

The sources come from different codes provided by Yu-Xiang Wang (UC Santa Barbara) and are associated with the article: "Trend Filtering on Graphs, JMLR, 2016". <https://sites.cs.ucsb.edu/~yuxiangw/resources.html>.

---

plot\_filter                      *Plot tight-frame filters.*

---

### Description

Plot tight-frame kernels/filters.

### Usage

plot\_filter(lmax, b, N = 1000)

### Arguments

lmax	Largest eigenvalues of the Laplacian matrix.
b	Parameter that control the number of scales.
N	Number of discretization points (by default N=1000).

plot\_graph

*Graph plot*

---

**Description**

Graph plot

**Usage**

```
plot_graph(z, size = 0.75)
```

**Arguments**

z	Graph data.
size	Dot size.

**See Also**[plot\\_signal](#)**Examples**

```
data(grid1)
plot_graph(grid1)
```

---

plot\_signal

*Plot a signal on top of a given graph*

---

**Description**

Plot a signal on top of a given graph

**Usage**

```
plot_signal(z, f, size = 0.75, limits = range(f))
```

**Arguments**

z	Graph data.
f	Signal to plot.
size	Dot size.
limits	Set colormap limits.

**See Also**[plot\\_graph](#)

**Examples**

```
f <- rnorm(length(grid1$xy[,1]))
plot_signal(grid1, f)
```

---

PSNR

*Peak Signal to Noise Ratio.*

---

**Description**

Compute the Peak Signal to Noise Ratio, defined by:

$$PSNR(x, y) = 10 \log_{10}(\max(\max(x), \max(y))^2 / |x - y|^2)$$

**Usage**

```
PSNR(x, y)
```

**Arguments**

x	Original reference signal/image.
y	Restored or noisy signal/image.

**Value**

Peak Signal to Noise ratio.

**See Also**

[SNR](#)

**Examples**

```
x <- cos(seq(0, 10, length=100))
y <- x + rnorm(100, sd=0.5)
PSNR(x, y)
```

randsignal                      *Generate random signal with varying regularity.*

---

**Description**

Generate  $f = A^k x_\eta / r^k$ , with A the adjacency matrix and  $x_\eta$  realization of Bernoulli random variables of parameter  $\eta$  and  $r$  the largest eigenvalue (in magnitude). The generation is carried out in sparse matrices in order to scale up.

**Usage**

```
randsignal(eta, k, A, r)
```

**Arguments**

eta	Smoothness parameter.
k	Smoothness parameter.
A	Adjacency matrix.
r	Optional argument corresponding to the largest eigenvalue of A (in magnitude).

**Value**

f output signal.

---

rlogo                              *R logo graph.*

---

**Description**

A dataset containing a graph based on the R logo.

**Usage**

```
rlogo
```

**Format**

list of 2 elements  
xy coordinates  
sA adjacency matrix



---

smoothmodulus	<i>Modulus of smoothness.</i>
---------------	-------------------------------

---

**Description**

Compute the modulus of smoothness of a graph signal.

**Usage**

```
smoothmodulus(f, A)
```

**Arguments**

f	Signal.
A	Adjacency matrix (sparse or dense).

**Examples**

```
data(grid1)
A <- grid1$A
x <- grid1$xy[,1]
f <- sin(x)
smoothmodulus(f, A)
```

---

SNR	<i>Signal to Noise Ratio.</i>
-----	-------------------------------

---

**Description**

Signal to Noise Ratio.

**Usage**

```
SNR(x, y)
```

**Arguments**

x	Original reference signal.
y	Restored or noisy signal.

**Value**

Signal to Noise ratio.

**See Also**

[PSNR](#)

**Examples**

```
x <- cos(seq(0, 10, length=100))
y <- x + rnorm(100, sd=0.5)
SNR(x, y)
```

---

 SUREthresh

*Stein's Unbiased Risk Estimate.*


---

**Description**

Adaptive Threshold Selection Using Principle of SURE (The irreducible variance term is not included, it does not change the position of the minimum).

**Usage**

```
SUREthresh(wcn, tresh, diagWWt, b, sigma, hatsigma, policy, keepwc = TRUE)
```

**Arguments**

wcn	Noisy wavelet coefficients.
tresh	Threshold values.
diagWWt	Weights.
b	Thresholding type (b=1: soft, b=2: JS).
sigma	Sd of the noise.
hatsigma	Estimator of the sd (if any).
policy	Dependent or uniform.
keepwc	Boolean allowing to export the coefficients of the frame after thresholding (TRUE by default).

**Value**

res a dataframe contening SURE, hatSURE and their respective minima.

**References**

de Loynes, B., Navarro, F., Olivier, B. (2021). Data-driven thresholding in denoising with Spectral Graph Wavelet Transform. *Journal of Computational and Applied Mathematics*, Vol. 389.

**See Also**

[SURE\\_MSEthresh](#)

---

SURE\_MSEthresh      *Stein's Unbiased Risk Estimate.*

---

### Description

Adaptive Threshold Selection Using Principle of SURE (The irreducible variance term is not included, it does not change the position of the minimum).

### Usage

```
SURE_MSEthresh(
  wcn,
  wcf,
  tresh,
  diagWwt,
  b,
  sigma,
  hatsigma,
  policy,
  keepwc = TRUE
)
```

### Arguments

wcn	Noisy wavelet coefficients.
wcf	True wavelet coefficients.
tresh	Threshold values.
diagWwt	Weights.
b	Thresholding type (b=1: soft, b=2: JS).
sigma	Sd of the noise.
hatsigma	Estimator of the sd (if any).
policy	Dependent or uniform.
keepwc	Boolean allowing to export the coefficients of the frame after thresholding (TRUE by default).

### Details

Note: - the calculation of the MSE is also included for comparison purpose.

### Value

res a dataframe contening MSE, SURE, hatSURE and their respective minima

## References

de Loynes, B., Navarro, F., Olivier, B. (2021). Data-driven thresholding in denoising with Spectral Graph Wavelet Transform. *Journal of Computational and Applied Mathematics*, Vol. 389.

## See Also

[SUREthresh](#)

---

swissroll

*Swiss roll graph generation*

---

## Description

Map the square  $[0, 1]^2$  in swiss roll for all  $x, y$  in  $[0, 1]^2$ , set

$$Sx = \pi \sqrt{(b^2 - a^2)x + a^2}$$

$$Sy = \pi(b^2 - a^2)y/2$$

## Usage

```
swissroll(N = 500, seed = NULL, a = 1, b = 4)
```

## Arguments

N	Number of points drawn.
seed	Optionally specify a RNG seed (for reproducible experiments).
a, b	Shape parameters.

## Value

N x 3 array for 3d points.

## See Also

[adjacency\\_mat](#)

## Examples

```
pts <- swissroll(N=500, seed=0, a=1, b=4)
```

---

synthesis	<i>Synthesis operator.</i>
-----------	----------------------------

---

**Description**

Compute the synthesis operator for coefficient coeff.

**Usage**

```
synthesis(coeff, tf)
```

**Arguments**

coeff	Transform coefficients.
tf	Frame coefficients.

**Value**

y Synthesis signal.

**See Also**

[analysis](#), [tight\\_frame](#)

---

tight_frame	<i>Tight-frame computation.</i>
-------------	---------------------------------

---

**Description**

Constructs tight-frame.

**Usage**

```
tight_frame(evalues, evector, b = 2)
```

**Arguments**

evalues	Eigenvalues of the Laplacian matrix.
evector	Eigenvectors of the Laplacian matrix.
b	Parameter that control the number of scales.

## References

- Coulhon, T., Kerkyacharian, G., & Petrushev, P. (2012). Heat kernel generated frames in the setting of Dirichlet spaces. *Journal of Fourier Analysis and Applications*, 18(5), 995-1066.
- Göbel, F., Blanchard, G., von Luxburg, U. (2018). Construction of tight frames on graphs and application to denoising. In *Handbook of Big Data Analytics* (pp. 503-522). Springer, Cham.
- de Loynes, B., Navarro, F., Olivier, B. (2021). Data-driven thresholding in denoising with Spectral Graph Wavelet Transform. *Journal of Computational and Applied Mathematics*, Vol. 389.

---

zetav

*Evaluates tight-frame kernel functions*

---

## Description

Evaluates kernel associated with the particular (Littlewood-Paley type) tight-frame construction, based on a unity partition, proposed in the reference papers.

## Usage

zetav(x, k, b)

## Arguments

- |   |   |
|---|---|
| x | Support to evaluate the kernel (vector).              |
| k | Scale index (scalar).                                 |
| b | Parameter that control the number of scales (scalar). |

## References

- Coulhon, T., Kerkyacharian, G., & Petrushev, P. (2012). Heat kernel generated frames in the setting of Dirichlet spaces. *Journal of Fourier Analysis and Applications*, 18(5), 995-1066.
- Göbel, F., Blanchard, G., von Luxburg, U. (2018). Construction of tight frames on graphs and application to denoising. In *Handbook of Big Data Analytics* (pp. 503-522). Springer, Cham.
- de Loynes, B., Navarro, F., Olivier, B. (2021). Data-driven thresholding in denoising with Spectral Graph Wavelet Transform. *Journal of Computational and Applied Mathematics*, Vol. 389.

# Index

## \* datasets

- grid1, 8
- minnesota, 12
- NYCdata, 12
- pittsburgh, 13
- rlogo, 16

adjacency\_mat, 2, 20

analysis, 3, 21

betathresh, 4

download\_graph, 4

eigendec, 5

eigensort, 5

forward\_sgwt, 6, 11

full, 7, 7

fullup, 7, 7

grid1, 8

GVN, 8, 9

HPFVN, 8, 9

inverse\_sgwt, 6, 10

laplacian\_mat, 3, 11

matmult, 11

minnesota, 12

NYCdata, 12

pittsburgh, 13

plot\_filter, 13

plot\_graph, 14, 14

plot\_signal, 14, 14

PSNR, 15, 17

randsignal, 16

rlogo, 16

smoothmodulus, 17

SNR, 15, 17

SURE\_MSEthresh, 18, 19

SUREthresh, 18, 20

swissroll, 3, 20

synthesis, 3, 21

tight\_frame, 3, 6, 11, 21, 21

zetav, 22