

Highly nonlinear approximations for signal representation

Manual for MATLAB routines

James BOWLEY, Laura REBOLLO-NEIRA and Zhiqiang XU
Aston University, Birmingham, B4 7ET, UK

<http://www.nonlinear-approx.info>

This project is supported by EPSRC (EP/D062632/1).



Contents

I	Pursuits	3
1	Pursuits	4
1.1	Function-Summary	4
1.2	Function-Description	4
1.2.1	BOOMP	4
1.2.2	BOOMPQ	5
1.2.3	KSwapping	5
1.2.4	OBOMP	6
1.2.5	OBOMPKSwaps	7
1.2.6	OMP	8
1.2.7	OMPFinalRefi	9
1.2.8	OMPKSwapRefi	9
1.2.9	OMPKSwapping	10
1.2.10	OMPKSwaps	11
1.2.11	OMPSwapping	12
1.2.12	OOMP	12
1.2.13	OOMPFinalRefi	13
1.2.14	OOMPKSwapRefi	14
1.2.15	OOMPKSwaps	14
1.2.16	Swapping	15
1.2.17	VFSwapping	16
2	Lq Minimization	17
2.1	Function-Summary	17
2.2	Function-Description	17
2.2.1	ALqMin	17
2.2.2	LqFOCUSS	18
2.2.3	RegFOCUSS	18
3	Examples	19
3.1	Example-Summary	19
3.2	Example-Description	19
3.2.1	exa_OBOMP	19
3.2.2	exa_OOMPKSwaps	19
3.2.3	exa_chirp	19
II	Projectors and Duals	20
4	Projectors	21
4.1	Function-Summary	21
4.2	Function-Description	21
4.2.1	ObliProj	21
4.2.2	OptObliProj	22
4.2.3	OrthProj	22

4.2.4	RegObliProj	23
5	Duals	24
5.1	Function-Summary	24
5.2	Function-Description	24
5.2.1	BioBack	24
5.2.2	BioDictDel	25
5.2.3	BioDictIns	25
5.2.4	BioFor	26
5.2.5	BioInsert	26
5.2.6	DRE	27
5.2.7	DREOr	27
5.2.8	DREOrp	28
5.2.9	FrDelete	28
5.2.10	FrInsert	29
5.2.11	FrInsertBlock	29
5.2.12	NBioDictIns	30
5.2.13	NBioInsert	30
6	Examples	31
6.1	Example-Summary	31
6.2	Example-Description	31
6.2.1	exa.ObliProj	31
6.2.2	exa.OptObliProj	31
6.2.3	exa.RegObliProj	31
III	Image Processing Tools	32
6.3	Function-Summary	33
6.4	Function-Description	33
6.4.1	CalcPSNR	33
6.4.2	DCos	33
6.4.3	DetectLines	33
6.4.4	GenerateHats	34
6.4.5	GenerateTrapezium	34
6.4.6	ImageApproximation	34
6.4.7	RemoveDependantAtoms	35
6.4.8	TranslatePrototype	35
6.5	Examples	36
6.6	Example-Summary	36
6.7	Example-Description	36
6.7.1	exa_image_approximation	36
6.7.2	exa_impulse_removal	36
IV	Spline Dictionaries	38
7	Uniform	39
7.1	Function-Summary	39
7.2	Function-Description	39
7.2.1	BSpline	39
7.2.2	DictSpline	40
7.2.3	Differ	40
7.2.4	ErrorTest	40
7.2.5	Green	40
7.2.6	NormDict	41
7.2.7	SplineLevel	41

7.2.8	SymSpline	41
7.2.9	TSpline	42
8	Non Uniform	43
8.1	Function-Summary	43
8.2	Function-Description	43
8.2.1	CutDic	43
8.2.2	NonBSpline	43
8.2.3	NonUniB	44
8.2.4	ProducePartition	44
9	Wavelets	45
9.1	Function-Summary	45
9.2	Function-Description	45
9.2.1	BuildDict	45
9.2.2	ElimBound	47
9.2.3	GDictFast	47
9.2.4	NumFun	48
9.2.5	SPL	48
9.2.6	STPoint	48
9.2.7	ScalLevel	49
9.2.8	SplineChuiWav	49
9.2.9	SplineScal	50
9.2.10	SplineWavelet	50
9.2.11	WavLevel	50

Preface

This document was written as an users guide to the computational tools delivered by the EPSRC funded project "Highly nonlinear approximations for sparse signal representation". More information about the project and tutorial material related to the routines of this manual are given in the website <http://www.nonlinear-approx.info>.

The project followed on of the previous EPSRC funded project "Biorthogonal techniques for optimal signal represeation. Thanks are due to Miroslav Andrlé for leaving the material of that project well organized, which facilitated the continuation of the work.

We would like to thank to Andreas Hartmann for his M2TEX script which has been used for generating most of this manual from our MATLAB sources.

Part I

Pursuits

Chapter 1

Pursuits

1.1 Function-Summary

BOOMP	Backward-Optimized Orthogonal Matching Pursuit
BOOMPQ	Backward-Optimized Orthogonal Matching and gives the orthonormal basis
KSwapping	extends Swapping to considering K swaps
OBOMP	Oblique Optimized Matching Pursuit
OBOMPKSwaps	Oblique Optimized Matching Pursuit with k swaps
OMP	Orthogonal Matching Pursuit
OMPFinalRefi	Refinement of OMP
OMPKSwapRefi	Refinement of OOMP by kswapping and backward deleting steps
OMPKSwapping	extends OMPSwapping to considering K swaps
OMPKSwaps	Optimized Orthogonal Matching Pursuit with k swaps
OMPSwapping	Swapping based refinement of OMP method
OOMP	Optimized Orthogonal Matching Pursuit
OOMPFinalRefi	refinement of OOMP by swapping and backward deleting steps.
OOMPKSwapRefi	Refinement of OOMP by kswapping and backward deleting steps
OOMPKSwaps	Optimized Orthogonal Matching Pursuit with k swaps
Swapping	Swapping based refinement of OMP methods
VFSwapping	Swapping based refinement of OMP methods (inner product implementation)

1.2 Function-Description

1.2.1 BOOMP

Backward-Optimized Orthogonal Matching Pursuit

Using the Least Square criterion at each step it eliminates one function from a given basis to have best possible representation in the reduced space. It also modifies the corresponding biorthogonal functions.

Usage: `[D, Di, beta, c] = BOOMP(f, D, beta, tol, No);`

Inputs:

f signal to represent
D set of chosen independent functions
beta set of biorthogonal functions to D
tol tolerance, desired difference between signal and its approx, (optional, default tol=1.0e-2)

No (optional) desired number of atoms in the decomposition if you want really No atoms set tol=0, it speeds the process

Outputs:

D new reduced set of independent functions
Di indices of atoms in new D w.r.t. to original D
beta biorthogonal functions to new D
c coefficients of the atomic decomposition

Note: this routine should be use only at the end of our selection process since it is not adapting (for the speed purposes) unselected dictionary functions. Thus any of our forward selection methods cannot be used after this.

References:

M. Andrlle, L. Rebollo-Neira, and E. Sagianos, "Backward-Optimized Orthogonal Matching Pursuit Approach", IEEE Signal Processing Letters, Vol (11,9), 705-708 (2004).

1.2.2 BOOMPQ

Backward-Optimized Orthogonal Matching and gives the orthonormal basis

Using the Least Square criterion at each step it eliminates one function from a given basis to have best possible representation in the reduced space. It also modifies the corresponding biorthogonal functions and orthonormal basis (obtained by modified Gram-Schmidt).

Usage: [D, Di, Q, beta, c] = BOOMPQ(f, D, Di, Q, beta, toli, No);
[D, Di, Q, beta, c] = BOOMPQ(f, D, Di, Q, beta, tol);

Inputs:

f analyzing signal D dictionary D(:,1:N) is the selected basis, N=size(beta,2)
Di indices of atoms Q Q(:,1:N) orthonormal set spanning D(:,1:N), Q(:,N+1:end) the rest of the dictionary orthogonalized w.r.t Q(:,1:N)
beta set of biorthogonal functions to D(:,1:N) tol tolerance, difference between signal and approx, (optional, default tol=1.0e-2)
No (optional) desired number of atoms in the decomposition if you want really No atoms set tol=0, it speeds the process

Outputs:

D rearranged dictionary
D(:,1:s) reduced basis, s=size(beta,2)
Di indices of atoms in new D w.r.t. to original D Q Q(:,1:s) orthonormal set spanning D(:,1:N), Q(:,s+1:end) the rest of the dictionary orthogonalized w.r.t Q(:,1:s)
beta biorthogonal functions to new D(:,1:s) c coefficients of the atomic decomposition

References:

M. Andrlle, L. Rebollo-Neira, and E. Sagianos, "Backward-Optimized Orthogonal Matching Pursuit Approach", IEEE Signal Processing Letters, Vol (11,9), 705-708 (2004).

1.2.3 KSwapping

extends Swapping to considering K swaps

Given an initial approximation of f, it improves upon the approximation by interchanging swi-pairs of atoms (swi from the approximation and swi from the dictionary) then (swi+1)-atoms and (swi+1)-atoms, (swi+2)-atoms and (swi+2)-atoms and so on up to

sws-atoms, unless the desired precision tol has been reached. (See Ref[1]). If the number of atoms involved in the swapping process is equal to sws and the stopping criterion based on the precision tol has not been reached the function returns the value re=0. Note: The inputs are obtainable by running OOMP first (see the example)

```
Usage: [ re, resid, D, Di, beta, C, Q ] = KSwapping( f, D, Di, Q, beta, C, swi,...
        sws, tol );
        [ re, resid, D, Di, beta, C, Q ] = KSwapping( f, D, Di, Q, beta, C );
```

Inputs:

```
f      signal to be decomposed
D      dictionary, first k functions D(:,1:k) are the selected basis
Di     indices of atoms in D with respect to the original dictionary
beta   biorthogonal functions to D(:,1:k), k=size(beta,2)
C      coefficients in the expansion
Q      Q(:,1:k) orthonormal basis spanning the same space as D(:,1:k), Q(:,k+1:end)
        unselected atoms subtracted by their component in D(:,1:k)
swi    minimum number of atoms to be swapped, default swi=1
sws    maximum number of atoms to be swapped
tol    tolerance for the approximation, default tol= 1e-8
```

Outputs:

```
re     convergence indicator: re=1 if the method converges within the given tol and
        re=0 otherwise
resid  vector of length sws to store the residuals at each swapping. The first
        component of resid is the residual when swi atoms are swapped, the second
        component is the residual when (swi+1) atoms are swapped and so on. If the
        swapping is started from swi atoms, resid is of length sws-swi+1
D      updated (re-arranged) dictionary, D(:,1:k) is the selected basis
Di     indices of atoms in D with respect to the original dictionary
beta   biorthogonal vectors to D(:,1:k)
C      coefficients in the expansion
Q      Q(:,1:k) orthonormal basis spanning the same space as D(:,1:k), Q(:,k+1:end)
        unselected atoms subtracted by their component in D(:,1:k)
```

References:

- [1] M. Andrle and L. Rebollo-Neira, "Improvement of Orthogonal Matching Pursuit strategies by Backward and Forward movements," in Proc. of the 31st International Conference on Acoustics, Speech, and Signal Processing (ICASSP'06)
- [2] M. Andrle and L. Rebollo-Neira, "A swapping-based refinement of orthogonal matching pursuit strategies", Signal Processing, Vol (86,3), 480-495 (2006)
- [3] L. Rebollo-Neira, "Measurements design and phenomena discrimination", J. Phys. A: Math. Theor. 42 (2009)

See also OOMPKSwaps OMPKSwaps OBOMPKSwaps Swapping OOMP

1.2.4 OBOMP

Oblique Optimized Matching Pursuit

Constructs an atomic decomposition which gives the oblique projection of a signal onto a subspace of the span of V along span of WC.

It first generates orthogonal projections onto the orthogonal complement of the span of WC and then find the atomic decomposition of the projected signal by the OOMP method.

For an example of how to use OBOMP to separate signal components run the code Exa_OBOMP

Usage: [fv] = OBOMP(f, V, WC);
[fv, Vnew, Di, beta, c, U, Q] = OBOMP(f, V, WC, err, No, opt, ind);

Inputs:

f signal to be projected
V dictionary for the space to project onto
WC dictionary spanning the space to project along
err error of each point of f (vector) or tolerance for the error's norm (scalar)
No (optional) maximal number of atoms to choose, if the number of chosen atoms equals to No, the routine will stop (default No=size(V,2))
ind (optional) indices determining the initial subspace
opt (optional) chose the method for computing the orthogonal projector with OrthProj (default opt=2 with tolerance for linear independence 1e-7)

Outputs:

Vnew the dictionary V rearranged according to the selection process Vnew(:,1:k) contains the atoms chosen into the atomic decomposition
Di indices of atoms in Vnew written w.r.t the original V
U Dictionary for the orthogonal complement of WC (U(:,1:k)) is a basis bi-orthogonal to beta)
Q the first k columns Q(:,1:k) gives an orthonormal basis for the span of U(:,1:k)
beta 'k' biorthogonal vectors to new V(:,1:k) and U(:,1:k) (in span of U(:,1:k))
c 'k' coefficients of the atomic decomposition for the oblique projection
fv oblique projection of f onto new V(:,1:k) along WC, i.e fv=Vnew(:,1:K)*c'

References

- [1] L. Rebollo-Neira, "Oblique Matching Pursuit", IEEE Signal Processing Letters, 14,10, 703-707 (2007).
- [2] L. Rebollo-Neira, "Measurements design and phenomena discrimination", J. Phys. A: Math. Theor. 42 (2009).

See also OBOMPKSwaps OOMP OOMPKSwaps

1.2.5 OBOMPKSwaps

Oblique Optimized Matching Pursuit with k swaps

Constructs an atomic decomposition which gives the oblique projection of a signal onto a subspace of the span of V, along span of WC, using OOMPKSwaps.

It first takes the orthogonal projection onto the orthogonal complement of the span of WC, then finds the atomic decomposition of the projected signal by the OOMP method and corrects with KSwapping to obtain the sought projection.

for an example on how to use OBOMPKSwaps to separate signal components run the code `exa_OBOMPKSwaps`

Usage: [re, resid, fv, Vnew, Di, beta, C, U, Q] = OBOMPKSwaps(f, V, WC, err,...
opt, No, ind, swi, sws, tols);
[re, resid, fv, Vnew, Di] = OBOMPKSwaps(f, V, W);

Inputs:

f signal to be projected
V dictionary for the space to project onto
WC dictionary spanning the space to project along

err (optional) error of each point of f, or tolerance for the error's norm, before starting the corrections (default err=0.0001*norm(f))
 opt (optional) chose the method for computing the orthogonal projector with OrthProj (default opt=2 with tolerance for linear Independence 1e-7)
 No (optional) maximal number of atoms to choose,(default No=size(D,2))
 ind (optional) indices determining the initial subspace
 swi (optional) minimum number of atoms to be swapped, (default swi=1)
 sws (optional) maximum number of atoms to be swapped, (default sws=size(beta,2))
 tols (optional) tolerance for the final approximation (default 0.0000001*norm(f))

Outputs:

re convergence indicator: re=1 if the method converges within the given tols and re=0 otherwise
 resid vector of length sws to store the residuals at each swapping. The first component of resid is the residual when swi atoms are swapped, the second component when (swi+1) atoms are swapped and so on.
 fv oblique projection of f onto new $V(:,1:k)$ along WC, i.e. $fv=Vnew(:,1:k)*C'$
 Vnew the dictionary V rearranged according to the selection process $Vnew(:,1:k)$ contains the atoms chosen to construct the atomic decomposition
 Di indices of atoms in Vnew written w.r.t the original V
 beta 'k' biorthogonal vectors to new $V(:,1:k)$ and $U(:,1:k)$ (spanning the same space as $U(:,1:k)$)
 C 'k' coefficients of the atomic decomposition for the oblique projection
 U Dictionary for the orthogonal complement of WC ($U(:,1:k)$) is a basis bi-orthogonal to beta)
 Q the first k columns $Q(:,1:k)$ gives an orthonormal basis for span of $U(:,1:k)$ and beta.

References:

[1] L. Rebollo-Neira, "Oblique Matching Pursuit", IEEE Signal Processing Letters, 14,10, 703-707 (2007)
 [2] L. Rebollo-Neira, "Measurements design and phenomena discrimination", J. Phys. A: Math. Theor. 42 (2009)

1.2.6 OMP

Orthogonal Matching Pursuit

It creates an atomic decomposition of a signal using OMP criterion. You can choose a tolerance, the number of atoms to take in or an initial subspace to influence the OMP algorithm.

Usage: [Dnew, Di, beta, c] = Omp(f, D, tol, No, ind);
 [Dnew, Di] = Omp(f, D, tol);

Inputs:

f analyzing signal
 D dictionary of normalized atoms
 tol desired distance between f and its approximation the routine will stop if $\|f' - D_{sub}(f \cdot \beta)'\| \cdot \sqrt{\delta} < \text{tol}$ where $\delta = 1/L$, L is number of points in a sample
 No (optional) maximal number of atoms to choose, if the number of chosen atoms equals to No, routine will stop (default No=size(D,2))
 ind (optional) indices determining the initial subspace,

Outputs:

D the dictionary D rearranged according to the selection process D(:,1:k) contains the atoms chosen into the atomic decomposition
 Di indices of atoms in new D written w.r.t the original D
 beta 'k' biorthogonal functions corresponding to new D(:,1:k)
 c 'k' coefficients of the atomic decomposition

References:

L. Rebollo-Neira and D. Lowe, "Optimized Orthogonal Matching Pursuit Approach", IEEE Signal Processing Letters, Vol(9,4), 137-140, (2002).

See also OMPF.

1.2.7 OMPFinalRefi

Refinement of OMP

It creates an atomic decomposition for approximation a signal using OMP method up to a given tolerance. When possible, the sparsity is improved afterwards by a combination of swapping and backward deleting steps.

You can choose a tolerance, the maximum number of atoms in the decomposition and an initial subspace to influence the OOMP algorithm. Non-selected atoms subtracted by their component in the chosen space are also available.

Usage: [D0, Di0] = OMPFinalRefi(f, D, tol);
 [DS0, Di0, beta0, c0, Q0] = OMPFinalRefi(f, D, tol, No, ind);

Inputs:

f analyzing signal
 D dictionary of normalized atoms
 tol desired distance between f and its approximation the routine will stop if $\text{norm}(f - D_{\text{sub}}(f * \text{beta})) * \sqrt{\text{delta}} < \text{tol}$ where $\text{delta} = 1/L$ (L is number of points in a sample) or $\text{delta} = 1$, which is the default in OOMP (to change this uncomment the corresponding line in OOMP)
 No (optional) maximal number of atoms to choose, if the number of chosen atoms equals to No, OOMP routine will stop (default No=size(D,2))
 ind (optional) indices determining the initial subspace for OOMP

Outputs:

DS0 the dictionary D rearranged according to the selection process DS0(:,1:k) contains the atoms chosen into the atomic decomposition
 Di0 indices of atoms in DS0 written w.r.t the original D
 Q0 Q(:,1:k) contains orthonormal functions spanning DS0(:,1:k) Q(:,k+1:N) contains DS0(:,k+1:N) subtracted by the projection onto the space generated by Q0(:,1:k) (resp. DS0(:,1:k))
 beta0 'k' biorthogonal functions corresponding to new DS0(:,1:k)
 c0 'k' coefficients of the atomic decomposition

1.2.8 OMPKSwapRefi

Refinement of OOMP by kswapping and backward deleting steps

It creates an atomic decomposition for approximation a signal using OOMP method up to a given tolerance. When possible, the sparsity is improved afterwards by a combination of kswapping and backward deleting steps.

You can choose a tolerance, the maximum number of atoms in the decomposition and an initial subspace to influence the OOMP algorithm. Non-selected atoms subtracted by their

component in the chosen space are also available.

```
Usage: [ D0, Di0 ] = OMPKSwapRefi( f, D, tol );
       [ DS0, Di0, Q0, beta0, c0 ] = OMPKSwapRefi( f, D, tol, No, ind );
```

Inputs:

```
f      analyzing signal
D      dictionary of normalized atoms
tol    desired distance between f and its approximation the routine will stop if
       norm(f'-Dsub*(f*beta)')*sqrt(delta)<tol where delta=1/L (L is number of points
       in a sample) or delta=1, which is the default in OOMPF (to change this
       uncomment the corresponding line in OOMPF)
No     (optional) maximal number of atoms to choose, if the number of chosen atoms
       equals to No, OOMP routine will stop (default No=size(D,2)
ind    (optional) indices determining the initial subspace for OOMP
swi    (optional) minimum number of atoms to swap (default=1)
sws    (optional) maximum number of atoms to swap (default=all)
[]     can be used for sws, swi, ind, No, and tol
```

Outputs:

```
DS0    the dictionary D rearranged according to the selection process DS0(:,1:k)
       contains the atoms chosen into the atomic decomposition
Di0    indices of atoms in DS0 written w.r.t the original D
beta0  'k' biorthogonal functions corresponding to new DS0(:,1:k)
c0     'k' coefficients of the atomic decomposition
Q0     Q(:,1:k) contains orthonormal functions spanning DS0(:,1:k), Q(:,k+1:N)
       contains DS0(:,k+1:N) subtracted by the projection onto the space generated by
       Q0(:,1:k) (resp. DS0(:,1:k))
```

1.2.9 OMPKSwapping

extends OMPSwapping to considering K swaps

Given an initial approximation of f, it improves upon the approximation by interchanging swi-pairs of atoms (swi from the approximation and swi from the dictionary) then (swi+1)-atoms and (swi+1)-atoms, (swi+2)-atoms and (swi+2)-atoms and so on up to sws-atoms, unless the desired precision tol has been reached. (See Ref[1]). If the number of atoms involved in the swapping process is equal to sws and the stopping criterion based on the precision tol has not been reached the function returns the value re=0. Note: The inputs are obtainable by running OMP first (see the example)

For an example on how to use the routine see `exa_OOMPKSwaps`

```
Usage: [ re, resid, D, Di, beta, C, Q ] = OMPKSwapping( f, D, Di, Q, beta, C, swi,...
       sws, tol );
       [ re, resid, D, Di, beta, C, Q ] = OMPKSwapping( f, D, Di, Q, beta, C );
```

Inputs:

```
f      analysing signal
D      dictionary, first k functions D(:,1:k) are the selected basis
Di     indices of atoms in D with respect to the original dictionary
Q      Q(:,1:k) orthonormal basis spanning the same space as D(:,1:k)
       Q(:,k+1:end) unselected atoms subtracted by their component in D(:,1:k)
beta   biorthogonal functions to D(:,1:k), k=size(beta,2)
C      coefficients in the expansion
swi    minimum number of atoms to be swapped, default swi=1
sws    maximum number of atoms to be swapped
```

tol tolerance for the approximation, default tol= 1e-8

Outputs:

re convergence indicator: re=1 if the method converges within the given tol and re=0 otherwise

resid vector of length sws to store the residuals at each swapping. The first component of resid is the residual when swi atoms are swapped, the second component is the residual when (swi+1) atoms are swapped and so on. If the swapping is started from swi atoms, resid is of length sws-swi+1

D updated (re-arranged) dictionary, D(:,1:k) is the selected basis

Di indices of atoms in D with respect to the original dictionary

beta biorthogonal vectors to D(:,1:k)

C coefficients in the expansion

Q Q(:,1:k) orthonormal basis spanning the same space as D(:,1:k)
Q(:,k+1:end) unselected atoms subtracted by their component in D(:,1:k)

References:

- [1] M. Andrlé and L. Rebollo-Neira, "Improvement of Orthogonal Matching Pursuit strategies by Backward and Forward movements," in Proc. of the 31st International Conference on Acoustics, Speech, and Signal Processing (ICASSP'06)
- [2] M. Andrlé and L. Rebollo-Neira, "A swapping-based refinement of orthogonal matching pursuit strategies", Signal Processing, Vol (86,3), 480-495 (2006)
- [3] L. Rebollo-Neira, "Measurements design and phenomena discrimination",% J. Phys. A: Math. Theor. 42 (2009)

See also OOMPkSwaps OMPkSwaps OBOMPkSwaps Swapping OOMP BOOMP OBOMP

1.2.10 OMPkSwaps

Optimized Orthogonal Matching Pursuit with k swaps

Constructs an approximation of f using OOMP and improves the approximation with KSwapping interchanging swi-pairs of atoms (swi from the approximation and swi from the dictionary) then (swi+1)-atoms and (swi+1)-atoms and so on up to sws-atoms, if tols is not reached. If the stopping criterion based on the precision tols is not reached re=0 is returned. (See KSwapping)

Usage: [re, resid, D, Di, beta, C, Q] = OOMPkSwaps(f, D);
[re, resid, D, Di, beta, C, Q] = OOMPkSwaps(f, D, err, No, ind, swi,...
sws, tols);

Inputs:

f signal to be represented

D dictionary for the space to project onto

err (optional) error of each point of f, or tolerance for the error's norm, before starting the swappings (default err=0.0001*norm(f))

No (optional) maximal number of atoms to choose, (default No=size(D,2))

ind (optional) indices determining the initial subspace

swi (optional) minimum number of atoms to be swapped, (default swi=1)

sws (optional) maximum number of atoms to be swapped, (default sws=size(beta,2))

tols (optional) tolerance for the final approximation (default 0.0000001*norm(f))

Outputs:

re convergence indicator: re=1 if the method converges within the given tols and re=0 otherwise

resid vector of length sws to store the residuals at each swapping. The first component of resid is the residual when swi atoms are swapped, the second

component when (swi+1) atoms are swapped and so on.
D updated (re-arranged) dictionary, $D(:,1:k)$ is the selected basis
Di indices of atoms in D with respect to the original dictionary
beta biorthogonal vectors to $D(:,1:k)$
C coefficients in the expansion
Q $Q(:,1:k)$ orthonormal basis spanning the same space as $D(:,1:k)$
 $Q(:,k+1:end)$ unselected atoms subtracted by their component in $D(:,1:k)$

References:

- [1] M. Andrlé and L. Rebollo-Neira, "Improvement of Orthogonal Matching Pursuit strategies by Backward and Forward movements," in Proc. of the 31st International Conference on Acoustics, Speech, and Signal Processing (ICASSP'06)
- [2] M. Andrlé and L. Rebollo-Neira, "A swapping-based refinement of orthogonal matching pursuit strategies", Signal Processing, Vol (86,3), 480-495 (2006)
- [3] L. Rebollo-Neira, "Measurements design and phenomena discrimination", J. Phys. A: Math. Theor. 42 (2009)
- [4] L. Rebollo-Neira and D. Lowe, "Optimized Orthogonal Matching Pursuit Approach", IEEE Signal Processing Letters, Vol(9,4), 137-140, (2002).

1.2.11 OMPSwapping

Swapping based refinement of OMP method

It interchanges at each step one atom from the atomic decomposition with another atom from the dictionary to improve the OMP approximation via adaptive biorthogonalization. At each step it modifies the biorthogonal vectors giving rise to the duals of selected atoms. The inputs are obtainable from the outputs of the OMP function

Usage: [D, Di, Q, beta] = OMPSwapping(f, D, Di, Q, beta);

Inputs:

D dictionary, first k functions $D(:,1:k)$ are the selected basis
Di indices of atoms in D with respect to the original dictionary
beta biorthogonal vectors to $D(:,1:k)$, $k=size(beta,2)$
Q orthonormal basis spanning the same space as $D(:,1:k)$

Outputs:

D updated (re-arranged) dictionary, $D(:,1:k)$ are the selected basis
beta biorthogonal functions to $D(:,1:k)$, $k=size(beta,2)$
Di indices of atoms in D with respect to the original dictionary
Q Q orthonormal basis spanning the same space as $D(:,1:k)$

References:

- M. Andrlé and L. Rebollo-Neira, "A swapping-based refinement of orthogonal matching pursuit strategies", Signal Processing, Vol 86, No 3, pp. 480-495, 2006.

See also OOMPSwapping, OOMPksSwaps, OMPksSwaps, OMPksSwapping

1.2.12 OOMP

Optimized Orthogonal Matching Pursuit

It creates an atomic decomposition of a signal using OOMP method [1]. You can choose a tolerance, the number of atoms to take in or an initial subspace to influence the OOMP algorithm. Non-selected atoms subtracted by their component in the chosen space are also available.

Usage: [Dnew, beta, Di] = OOMP(f, D, tol);

```
[ Dnew, beta, Di, c, Q ] = OOMP( f, D, tol, No, ind );
```

Inputs:

f signal to be represented
D dictionary of atoms
tol desired distance between f and its approximation the routine will stop if $\text{norm}(f' - D_{\text{sub}}(f * \text{beta})') * \sqrt{\text{delta}} < \text{tol}$ where $\text{delta} = 1/L$, L is number of points in a sample
No (optional) maximal number of atoms to choose, if the number of chosen atoms equals to No, routine will stop (default No=size(D,2))
ind (optional) indices determining the initial subspace,

Outputs:

D the dictionary D rearranged according to the selection process D(:,1:k) contains the atoms chosen into the atomic decomposition
beta 'k' biorthogonal functions corresponding to new D(:,1:k)
Di indices of atoms in new D written w.r.t the original D
c 'k' coefficients of the atomic decomposition
Q Q(:,1:k) contains orthonormal functions spanning new D(:,1:k), Q(:,k+1:N) contains new D(:,k+1:N) subtracted by the projection onto the space generated by Q(:,1:k) (resp. D(:,1:k))

References:

- [1] L. Rebollo-Neira and D. Lowe, "Optimized Orthogonal Matching Pursuit Approach", IEEE Signal Processing Letters, Vol(9,4), 137-140, (2002).
For the current implementation:
[2] M. Andrle and L. Rebollo-Neira, "A swapping-based refinement of orthogonal matching pursuit strategies", Signal Processing, Vol 86, No 3, pp. 480-495, (2006).

See also OMP Swapping OOMPKSwaps OMPKSwaps OOMPFinalRefi BOOMP OBOMP

1.2.13 OOMPFinalRefi

refinement of OOMP by swapping and backward deleting steps.

It creates an atomic decomposition for approximation a signal using OOMP method up to a given tolerance. When possible, the sparsity is improved afterwards by a combination of swapping and backward deleting steps.

You can choose a tolerance, the maximum number of atoms in the decomposition and an initial subspace to influence the OOMP algorithm. Non-selected atoms subtracted by their component in the chosen space are also available.

```
Usage:    [ D0, Di0 ] = OOMPFinalRefi( f, D, tol );
          [ DS0, Di0, beta0, c0, Q0 ] = OOMPFinalRefi( f, D, tol, No, ind);
```

Inputs:

f analyzing signal
D dictionary of normalized atoms
tol desired distance between f and its approximation the routine will stop if $\text{norm}(f' - D_{\text{sub}}(f * \text{beta})') * \sqrt{\text{delta}} < \text{tol}$ (L is number of points in a sample) or $\text{delta} = 1$, which is the default in OOMP (to change this uncomment the corresponding line in OOMP)
No (optional) maximal number of atoms to choose, if the number of chosen atoms equals to No, OOMP routine will stop (default No=size(D,2))
ind (optional) indices determining the initial subspace for OOMP
[] can be used for ind, No tol

Outputs:

DS0 the dictionary D rearranged according to the selection process DS0(:,1:k) contains the atoms chosen into the atomic decomposition
Di0 indices of atoms in DS0 written w.r.t the original D
Q0 Q(:,1:k) contains orthonormal functions spanning DS0(:,1:k), Q(:,k+1:N) contains DS0(:,k+1:N) subtracted by the projection onto the space generated by Q0(:,1:k) (resp. DS0(:,1:k))
beta0 'k' biorthogonal functions corresponding to new DS0(:,1:k)
c0 'k' coefficients of the atomic decomposition

1.2.14 OOMPksSwapRefi

Refinement of OOMP by kswapping and backward deleting steps

It creates an atomic decomposition for approximation a signal using OOMP method up to a given tolerance. When possible, the sparsity is improved afterwards by a combination of kswapping and backward deleting steps.

You can choose a tolerance, the maximum number of atoms in the decomposition and an initial subspace to influence the OOMP algorithm. Non-selected atoms subtracted by their component in the chosen space are also available.

Usage: [D0, Di0] = OOMPksSwapRefi(f, D, tol);
[DS0, Di0, Q0, beta0, c0] = OOMPksSwapRefi(f, D, tol, No, ind);

Inputs:

f analyzing signal
D dictionary of normalized atoms
tol desired distance between f and its approximation the routine will stop if $\|f - D_{\text{sub}}(f \cdot \beta)\| \cdot \sqrt{\delta} < \text{tol}$ where $\delta = 1/L$ (L is number of points in a sample) or $\delta = 1$, which is the default in OOMP (to change this uncomment the corresponding line in OOMP)
No (optional) maximal number of atoms to choose, if the number of chosen atoms equals to No, OOMP routine will stop (default No=size(D,2))
ind (optional) indices determining the initial subspace for OOMP
swi (optional) minimum number of atoms to swap (default=1)
sws (optional) maximum number of atoms to swap (default=all)
[] can be used for sws, swi, ind, No, and tol

Outputs:

DS0 the dictionary D rearranged according to the selection process DS0(:,1:k) contains the atoms chosen into the atomic decomposition
Di0 indices of atoms in DS0 written w.r.t the original D
beta0 'k' biorthogonal functions corresponding to new DS0(:,1:k)
c0 'k' coefficients of the atomic decomposition
Q0 Q(:,1:k) contains orthonormal functions spanning DS0(:,1:k), Q(:,k+1:N) contains DS0(:,k+1:N) subtracted by the projection onto the space generated by Q0(:,1:k) (resp. DS0(:,1:k))

1.2.15 OOMPksSwaps

Optimized Orthogonal Matching Pursuit with k swaps

Constructs an approximation of f using OOMP and improves the approximation with KSwapping interchanging swi-pairs of atoms (swi from the approximation and swi from the dictionary) then (swi+1)-atoms and (swi+1)-atoms and so on up to sws-atoms, if tols is not reached. If the stopping criterion based on the precision tols is not reached re=0

is returned. (See KSwapping)

For an example on how to use OOMPKSwargs to represent a signal run de code `exa_OOMPKSwargs`

```
Usage: [ re, resid, D, Di, beta, C, Q ] = OOMPKSwargs( f, D );  
       [ re, resid, D, Di, beta, C, Q ] = OOMPKSwargs( f, D, err, No, ind, swi,...  
           sws, tols );
```

Inputs:

f signal to be represented
D dictionary for the space to project onto
err (optional) error of each point of f, or tolerance for the error's norm, before starting the swappings (default `err=0.0001*norm(f)`)
No (optional) maximal number of atoms to choose, (default `No=size(D,2)`)
ind (optional) indices determining the initial subspace
swi (optional) minimum number of atoms to be swapped, (default `swi=1`)
sws (optional) maximum number of atoms to be swapped, (default `sws=size(beta,2)`)
tol (optional) tolerance for the final approximation (default `0.0000001*norm(f)`)

Outputs:

re convergence indicator: `re=1` if the method converges within the given tols and `re=0` otherwise
resid vector of length `sws` to store the residuals at each swapping. The first component of `resid` is the residual when `swi` atoms are swapped, the second component when `(swi+1)` atoms are swapped and so on.
D updated (re-arranged) dictionary, `D(:,1:k)` is the selected basis
Di indices of atoms in D with respect to the original dictionary
beta biorthogonal vectors to `D(:,1:k)`
C coefficients in the expansion
Q `Q(:,1:k)` orthonormal basis spanning the same space as `D(:,1:k)`, `Q(:,k+1:end)` unselected atoms subtracted by their component in `D(:,1:k)`

References:

- [1] M. Andrle and L. Rebollo-Neira, "Improvement of Orthogonal Matching Pursuit strategies by Backward and Forward movements," in Proc. of the 31st International Conference on Acoustics, Speech, and Signal Processing (ICASSP'06)
- [2] M. Andrle and L. Rebollo-Neira, "A swapping-based refinement of orthogonal matching pursuit strategies", Signal Processing, Vol (86,3), 480-495 (2006)
- [3] L. Rebollo-Neira, "Measurements design and phenomena discrimination", J. Phys. A: Math. Theor. 42 (2009)

1.2.16 Swapping

Swapping based refinement of OMP methods

It interchange at each step one atom from the atomic decomposition for another atom from the dictionary to improve the signal approximation. Similarly at each step it modifies the biorthogonal vectors and the unselected atoms from the dictionary subtracted by their component from the selected space. The process is carried out until the approximation error will not increase.

```
Usage: [ D, Di, Q, beta ] = Swapping( f, D, Di, Q, beta );
```

Inputs:

D dictionary, first `k` functions `D(:,1:k)` are the selected basis
Di indices of atoms in D with respect to the original dictionary

beta biorthogonal functions to $D(:,1:k)$, $k=\text{size}(\text{beta},2)$
 Q $Q(:,1:k)$ orthonormal basis spanning the same space as $D(:,1:k)$
 $Q(:,k+1:\text{end})$ unselected atoms subtracted by their component in $D(:,1:k)$

Outputs:

D updated (re-arranged) dictionary, $D(:,1:k)$ are the selected basis
 beta biorthogonal functions to $D(:,1:k)$, $k=\text{size}(\text{beta},2)$
 Di indices of atoms in D with respect to the original dictionary
 Q $Q(:,1:k)$ orthonormal basis spanning the same space as $D(:,1:k)$
 $Q(:,k+1:\text{end})$ unselected atoms subtracted by their component in $D(:,1:k)$

References:

M. Andrlé and L. Rebollo-Neira, "A swapping-based refinement of orthogonal matching pursuit strategies", *Signal Processing*, Vol 86, No 3, pp. 480-495, 2006.

See also KSwapping, VFSwapping.

1.2.17 VFSwapping

Swapping based refinement of OMP methods (inner product implementation)

It interchange at each step one atom from the atomic decomposition for another atom from the dictionary to improve the signal approximation. The process is carried out until the approximation error will not increase. The routine is not modifying biorthogonal functions or unselected atoms subtracted by the component in the selected space but only several related inner product matrices. See Alg. 4b in the reference below.

Usage: VFSwapping(f, D);

Inputs:

f signal
 D dictionary

These inputs and all outputs are realized through global variables AL LL LF J IJ I

I set of all indices
 J set of indices (subset of I) which are not in the basis
 IJ set of indices (subset of I) which are in the basis
 AL inner products between dictionary D and lambdas
 LL inner products between $\text{lambda}(IJ)$, between biorthogonal functions to $D(:,IJ)$
 LF inner products between lambda and signal f

Note: $\text{lambda}(IJ)$ means biorthogonal functions to $D(IJ)$
 $\text{lambda}(J)$ means $D(J)$ subtracted by their component in selected basis $D(IJ)$

References:

M. Andrlé and L. Rebollo-Neira, "A swapping-based refinement of orthogonal matching pursuit strategies", *Signal Processing*, Vol (86,3), 480-495 (2006).

See also Swapping, KSwapping.

Chapter 2

Lq Minimization

2.1 Function-Summary

ALqMin	adaptive lq like minimization
LqFOCUSS	solves for x in $f = Dx$ by minimizing the lq^q norm by the method FOCUSS
RegFOCUSS	solves for xc in $f = Dxc$ by minimizing $\ xc\ _q^q + lam(f - Dxc)$

2.2 Function-Description

2.2.1 ALqMin

adaptive lq like minimization

It gives an approximated solution to an underdetermined least square problem by minimization of the lq^q -like quantity. The algorithm evolves by adaptive selection of a subset of normal equations as linear constraints for the minimization process [1]. The constrained minimization is implemented by the function LQ_FOCUSS, which applies the FOCUSS algorithm [2].

Usage: [xc] = ALqMin(fw, U, q);
 [xc, ki, resn] = ALqMin(fw, U, q, tol, No, itmax);

Inputs:

fw data to be modeled by $fw \sim U \cdot xc$
U matrix in the model above
q specifies the value q for the lq norm
tol the routine will stop if $\text{norm}(fw - U \cdot xc) < \text{tol}$ (default tol=1e-8)
No maximum number of constraints (stopping condition) (default No=size(U,2))
itmax maximal number of iterations for the focuss algorithm (default itmax=30)

Outputs:

xc solution of the lq minimization
Nc total number of normal equations that have been considered
resn value of $\text{norm}(fw - U \cdot xc) \cdot \text{sqrt}(\text{delta})$

References:

- [1] L. Rebollo-Neira and A. Plastino, Nonlinear non-extensive approach for identification of structured information, Physica A, 2009
- [2] B.D. Rao and K. Kreutz-Delgado, An Affine Scaling Methodology for Best Basis Selection, IEEE Trans. Sig. Proc. 47 (1999) 187--200

2.2.2 LqFOCUSS

solves for x in $f = Dx$ by minimizing the lq^q norm by the method FOCUSS

```
Usage:  [ xc ] = LqFOCUSS( f, D, xo, q )
        [ xc ] = LqFOCUSS( f, D, xo, q, tol, itmax )
```

Inputs:

```
f      data modelled as f= D xc
D      matrix in the model
xo     initial solution
q      value for q in the lq norm like measure
tol    tolerance for convergence (default tol = 1e-8)
itmax  maximum number of iterations (default itmax=30)
```

Outputs:

```
xc     solution of minimum lq norm in the model f= D*xc
```

Reference

[1] B.D. Rao and K. Kreutz-Delgado, An Affine Scaling Methodology for Best Basis Selection, IEEE Trans. Sig. Proc. 47 (1999) 187--200

2.2.3 RegFOCUSS

solves for xc in $f = Dxc$ by minimizing $\|xc\|_q^q + lam(f - Dxc)$

It applies the algorithm given in FOCUSS [1]

```
Usage:  [xc] = RegFOCUSS( f, D, q )
        [xc] = RegFOCUSS( f, D, q, lam, tol, itmax, xo )
```

Inputs:

```
f      data modelled as f= D xc
D      matrix in the model
q      value for q in the lq norm like measure
lam    regularization parameter (default lam = 1e-8)
tol    tolerance for convergence (default tol = 1e-8)
itmax  maximum number of iterations (default itmax=30)
xo     initial solution (default all the entris equal to 1)
[]     can be used for itmax, tol and lam
```

Outputs

```
xo     regularized solution of f= D xc
```

References

[1] B.D. Rao, K. Engan, S. F. Cotter, J. Palmer, K. Kreutz-Delgado, Subset selection in noise based on diversity measure minimization, IEEE Transactions on Signal Processing, 51, 3 (2003) 760-- 770, 10.1109/TSP.2002.808076.

Chapter 3

Examples

3.1 Example-Summary

<code>exa_OBOMP</code>	using the OBOMP function
<code>exa_OOMPkSwaps</code>	improves upon the OOMP approximation by k swappings
<code>exa_chirp</code>	adapted spline approximation of the chirp signal

3.2 Example-Description

3.2.1 `exa_OBOMP`

using the OBOMP function

It separates the component `fv` in `V` from `f=fv+fw`; with `fw` in `WC` (uses OBOMP)

3.2.2 `exa_OOMPkSwaps`

improves upon the OOMP approximation by k swappings

Creates a cardinal B-spline dictionary and a the signal `f` as a random superposition of 95 splines. Calls `OOMP_KSWAPS` (which uses `KSwapping`) to improve the OOMP approximation by k swappings, untill `tols=1e-9*norm(f)` is reached.

3.2.3 `exa_chirp`

adapted spline approximation of the chirp signal

This example generates a nonuniform spline space adapted to a chirp signal and constructs a dictionary for sparse approximation of the chirp through refinements of OOMP and OMP approaches.

Part II

Projectors and Duals

Chapter 4

Projectors

4.1 Function-Summary

ObliProj	constructs an oblique projection matrix onto the span of the columns of V along the span of the columns of Wperp
OptObliProj	regularizes the oblique projector of a give signal by truncation of singular values
OrthProj	construct an orthogonal projection matrix onto the span of the columns of D.
RegObliProj	regularizes the oblique projection of a given noisy signal by truncation of singular valueas

4.2 Function-Description

4.2.1 ObliProj

constructs an oblique projection matrix onto the span of the columns of V along the span of the columns of Wperp

for opt=[1,1] computes the projector as $E=V*W$, where $W=pinv(U'*V)*U'$
with $U=V-orthProj_{\{Wperp\}} V$

for opt=[2,1] computes the projector as $E=V*W$, where $W=pinv(U'*U)*U'$
with $U=V-OrthProj_{\{Wperp\}} V$

for opt=[3,1] computes the projector as $E=V*W$, where $W=pinv(U)'$
with $U=V-OrthProj_{\{Wperp\}} V$

for opt=[1,2] computes the projector as $E=V*W$, where $W=pinv(Q'*V)*Q'$
with $U=V-OrthProj_{\{Wperp\}}$ and $Q=DREOr(U)$

for opt=[1,3] computes the projector as $E=V*W$, where $W=pinv(Q'*V)*Q'$
with $U=V-OrthProj_{\{Wperp\}}$ and $Q=qr(U)$

for opt=[1,4] computes the projector as $E=V*W$, where $W=pinv(Q'*V)*Q'$
with $U=V-OrthProj_{\{Wperp\}}$ and $Q=orth(U)$

for opt=[2,2] computes the projector as $E=V*W$, where $W=pinv(Q'*U)*Q'$
with $U=V-OrthProj_{\{Wperp\}}$ and $Q=DREOr(U)$

for opt=[2,3] computes the projector as $E=V*W'$, where $W'=pinv(Q'*U)*Q'$
with $U=V-OrthProj_{\{Wperp\}}$ and $Q=qr(U)$

for opt=[2,4] computes the projector as $E=V*W'$, where $W'=pinv(Q'*U)*Q'$
with $U=V-OrthProj_{\{Wperp\}}$ and $Q=orth(U)$

Usage: [W, U, E] = ObliProj(V, Wperp, opt, tol, ind);
[W, U, E] = ObliProj(V, Wperp);

Inputs:

V matrix the columns of which span then space to project onto
Wperp matrix the columns of which span then space to project along
opt array to chose the method to calculate the projector (see above) default
opt=[3,1]
tol if opt=[1,2], or [2,2] tol is the torance set for considering linearly
independent columns [default tol= 1.0000e-7]
ind (optional) the indices of vectors to start the orthogonalization (see DREOr)
[] can be used for ind, tol and opt

Outputs:

W matrix producing $E=U*W$;
U matrix producing $E=U*W$;
E Projector onto span of columns of V onto columns of Wperp

see orth DREOrp DREOr qr

4.2.2 OptObliProj

regularizes the oblique projector of a give signal by truncation of singular values

The projection of f onto span of V along span of WC is regularized by truncation of
singular values- the number of singular values is decided by minimizing:

$$||P_W f' - P_W E_{\{VWC\}}f'||$$

where P_W is the orthogonal projector onto W (the orthogonal complement of span WC) and
 $E_{\{V,WC\}}$ is the oblique projector onto span V along span WC.

Usage: [fe, c, lm] = OptObliProj(D, WC, f, opt, eps);
[fe, c, lm] = OptObliProj(D, WC, f);

Inputs:

V matrix, the columns of which span the space to project onto
WC matrix, the columns of which span the space to project along
f vector, with signal to be projected
opt equivalent role as in ObliProj and (for details see there) but some of them
may not always be good here default opt=[3,1].
eps minimum eigenvalue to be considered nonzero
[] can be used for eps or/and opt

Outputs:

fe regularized oblique projection of f
c coefficients in the decomposition $fe=V*c$
lm resulting number of nonzero eigenvalues to calculate fe

See also ObliProj RegObliProj OrthProj

4.2.3 OrthProj

construct an orthogonal projection matrix onto the span of the columns of D.

for opt=1 it uses the matlab function orth to orthogonalize D
 for opt=2 it uses the routine DREOrp (recommended when the columns of D are quasi
 Linearly Dependent up tolerance tol, see DREOr)
 for opt=3 it uses the QR decomposition matlab function.

Usage: [P, Q] = OrthProj(D, opt, tol, ind);
 [P, Q] = OrthProj(D);

Inputs:

D matrix the columns of which is a dictionary of normalized atoms
 opt to chose the method to calculate the projector (see above) default for opt=3
 tol (optional) the tolerance set for considering linearly dependant columns
 [default tol = 1.0000e-7]
 ind (optional) the indices of vectors to start the orthogonalization (see DreOr)

Outputs:

Q Orthogonal vectors such that P=Q*Q'
 P Projector onto span of the columns of Q

See also DREOrp DREOr qr orth

4.2.4 RegObliProj

regularizes the oblique projection of a given noisy signal by truncation of singular valueas

The regularization tries to fulfill:

$$\|P_W f' - P_W E_{\{VWC\}} f'\| \leq \|P_W \text{err}'\|,$$

where P_W is the orthogonal projector onto W (the orthogonal complement of span WC) and E_{V,W,C} is the oblique projector onto span V along span WC.

Usage: [fe, c, lm] = RegObliProj(D, WC, f, err, opt, No);
 [fe, c, lm] = RegObliProj(D, WC, f);

Inputs:

V matrix, the columns of which span the space to project onto
 WC matrix, the columns of which span the space to project along
 f vector, with signal to be projected
 opt equivalent role as in ObliProj (for details see there) default opt=[1,2] (with
 tol_orth= 1e-7 for DREOr)
 err (optional) error of each point of f, or tolerance for the error's norm default
 err=ones(size(f))*5e-7
 No maximum number of eigenvalues to consider default all
 [] can be used for err, opt, or No

Outputs:

fe regularized oblique projection of f
 c coefficients in the decomposition fe=V*c
 lm resulting number of nonzero eigenvalues to calculate fe

Chapter 5

Duals

5.1 Function-Summary

BioBack	deletes the requested vector j from a given basis taken from a dictionary
BioDictDel	deletes a vector from a basis selected from a given dictionary and appropriately modifies biorthogonal functions, orthonormal functions spanning the same space as the basis, and unselected dictionary atoms subtracted by their components in the selected basis.
BioDictIns	enlarges a basis selected from a given dictionary by one vector
BioFor	enlargers the dual/biorthogonal basis enlarger by one vector
BioInsert	adds an atom to a basis. It also appropriately modifies the corresponding biorthogonal basis and orthonormal basis (obtained by modified Gram-Schmidt).
DRE	Dictionary Redundancy Elimination
DREOr	uses DRE method to produce and orthogonal basis from a dictionary and gives dictionary's indices of the atoms spanning the space.
DREOrp	uses Dre method to produce and orthogonal basis from a dictionary.
FrDelete	deletes the requested vector from a given frame
FrInsert	adds a vector to a frame. It also appropriately modifies the corresponding dual frame.
FrInsertBlock	adds vectors to a basis and gives the duals spanning the same space
NBioDictIns	enlarges a basis selected from a given dictionary by one vector. It modifies the biorthogonal basis for the same space and gives the projection of the remaining atoms onto the orthogonal complementary space
NBioInsert	adds an atom to a basis and modifies the biorthogonal basis for the same space

5.2 Function-Description

5.2.1 BioBack

deletes the requested vector j from a given basis taken from a dictionary

Modifies the corresponding biorthogonal basis and orthonormal basis (obtained by modified Gram-Schmidt) and returned the re-ordered dictionary (this is the only difference with `biodelete`, which does not deal with the whole dictionary).

Usage: `[D, psin, beta] = BioBack(D, psin, beta, j);`

Inputs:

`D` Dictionary, first `kb` vectors `D(:,1:kb)` are the selected basis

psin orthonormal basis spanning the same space as $D(:,1:kb)$ $kb=size(psin,2)$
 beta biorthogonal basis to $D(:,1:kb)$, $kb=size(beta,2)$
 j index of function to eliminate

Outputs:

D updated (rearranged) dictionary ($D(:,1:kb-1)$ is the new basis)
 psin updated orthonormal basis spanning the same space as $D(:,1:kb-1)$
 beta updated biorthogonal basis to $D(:,1:kb-1)$

References:

L. Rebollo-Neira, "Recursive bi-orthogonalisation approach and orthogonal projectors",
 math-ph/0209026 (2002).

See also NBioDelete, NBioDictDel, BioDictDel.

5.2.2 BioDictDel

deletes a vector from a basis selected from a given dictionary and appropriately modifies biorthogonal functions, orthonormal functions spanning the same space as the basis, and unselected dictionary atoms subtracted by their components in the selected basis.

The dictionary is then rearranged to have one to one correspondence with beta (dual functions) and psin.

Usage: [D, psin, beta] = BioDictDel(D, psin, beta, j);

Inputs:

D dictionary, first kb functions are the selected basis
 psin psin(:,1:kb) orthonormal functions spanning the same space as $D(:,1:kb)$
 psin(:,kb+1:end)= $D(:,kb+1:end)$ without component from $D(:,1:kb)$
 beta kb biorthogonal functions to $D(:,1:kb)$, $kb=size(beta,2)$
 j index of function to eliminate

Outputs:

D updated (rearranged) dictionary
 psin psin(:,1:kb-1) updated (recalculated) orthonormal functions spanning the same space as the chosen atoms psin(:,kb:end) updated (recalculated) unchosen dictionary atoms subtracted by their components in the selected basis.
 beta updated biorthogonal functions to $D(:,1:kb-1)$

References:

L. Rebollo-Neira, "Recursive bi-orthogonalisation approach and orthogonal projectors",
 math-ph/0209026 (2002).

See also: NBioDictDel, BioDelete, NBioDelete.

5.2.3 BioDictIns

enlarges a basis selected from a given dictionary by one vector

It appropriately modifies the biorthogonal functions and unselected dictionary atoms subtracted by their components in the selected basis. It also updates the set of orthonormal functions spanning the same space as chosen atoms.

Usage: [Q, beta] = BioDictIns(D, Q, beta, k);

Inputs:

D dictionary, rearranged in such way that $D(:,1:k-1)$ are the selected atoms

$D(:,k)$ is the atom to add into the basis
Q $Q(:,1:k-1)$ = orthonormal basis to $D(:,1:k-1)$ $Q(:,k:end)=D(:,k:end)$ without component from $D(:,1:k-1)$
beta biorthogonal functions to $D(:,1:k-1)$
k k-th atom of D to incorporate it says that first $k-1$ atoms are already in basis

Outputs:

Q $Q(:,1:k)$ = orthonormal basis to $D(:,1:k)$ $Q(:,k+1:end)=D(:,k+1:end)$ without component from $D(:,1:k)$
beta updated biorthogonal functions to $D(:,1:k)$

References:

L. Rebollo-Neira, "Recursive bi-orthogonalisation approach and orthogonal projectors", math-ph/0209026 (2002).

See also NBioDictIns, BioInsert, NBioInsert.

5.2.4 BioFor

enlarges the dual/biorthogonal basis enlarger by one vector

It modifies the biorthogonal basis and updates the set of orthonormal vectors spanning the same space as the the enlaged basis.

Usage: [Q, beta] = BioFor(D, Q, beta, k);

Inputs:

D dictionary, rearranged in such way that $D(:,1:k-1)$ are the basis vectors and $D(:,k)$ is the atom to add into the basis
Q $Q(:,1:k-1)$ = orthonormal basis for the span of $D(:,1:k-1)$
beta biorthogonal basis to $D(:,1:k-1)$
k k-th element of D to incorporate in the basis it implies that the first $k-1$ vectors are already in the basis

Outputs:

Q $Q(:,1:k)$ = orthonormal basis for span of $D(:,1:k)$
beta updated biorthogonal basis to $D(:,1:k)$

References:

L. Rebollo-Neira, "Recursive bi-orthogonalisation approach and orthogonal projectors", math-ph/0209026 (2002).

See also NBioDictIns, BioInsert, NBioInsert

5.2.5 BioInsert

adds an atom to a basis. It also appropriately modifies the corresponding biorthogonal basis and orthonormal basis (obtained by modified Gram-Schmidt).

Usage: [D, psin, beta] = BioInsert(D, psin, beta, atom, tol);

Inputs:

D already selected basis
psin orthonormal basis spanning the same space as D
beta biorthogonal basis to D
atom new atom to be incorporated into basis
tol tolerance (optional parameter) to decide linear dependence default value =

1.0000e-7

Outputs:

D updated basis
psin updated orthonormal basis spanning the same space as D
beta updated biorthogonal functions to D

References:

L. Rebollo-Neira, "Recursive bi-orthogonalisation approach and orthogonal projectors", math-ph/0209026 (2002).

See also NBioInsert, NBioDictIns, BioDictIns.

5.2.6 DRE

Dictionary Redundancy Elimination

With help of column pivoting it tries to choose a stable basis from a given dictionary.

Usage: [Dnew, Di, Q, beta] = DRE(D, tol, ind);
[Dnew, Di] = DRE(D);

Inputs:

D dictionary of normalized atoms
tol tolerance set for considering as linearly dependent atom [default tol=1.0000e-7]
ind (optional) indices determining the initial subspace
[] can be used for tol and ind

Outputs:

D sub-dictionary extracted from D containing linearly independent atoms
Di indices of atoms in new D w.r.t to original D
Q orthonormal functions spanning the same space as new D
beta biorthogonal functions to new D

References:

L. Rebollo-Neira, "Dictionary redundancy elimination", IEE Proceedings - Vision, Image and Signal Processing, Vol(151,1), 31-34 (2004).

See also DREOr DREOrp Biorthog.

5.2.7 DREOr

uses DRE method to produce an orthogonal basis from a dictionary and gives dictionary's indices of the atoms spanning the space.

The difference with DREOrp is that it gives Di (see below)

Implement column pivoting to choose a stable orthogonal basis from a given set, which could be redundant, called "dictionary"

Usage: [Q, Di] = DREOr(D, tol, ind);
[Q, Di] = DREOr(D, tol);
[Q, Di] = DREOr(D);

Inputs:

D matrix the columns of which is a dictionary of normalized atoms
 tol tolerance set for considering as linearly dependent columns [default tol=1.0000e-7]
 ind (optional) indices determining the initial subspace
 [] can be used for tol and ind

Outputs:

Q orthonormal vectors spanning the same space as D (up to tol)
 Di indices of linearly independent atoms that have been orthogonalized

References:

L. Rebollo-Neira, "Dictionary redundancy elimination", IEE Proceedings - Vision, Image and Signal Processing, Vol(151,1), 31-34 (2004).

See also DRE DREOrp and Biorthog

5.2.8 DREOrp

uses Dre method to produce and orthogonal basis from a dictionary.

The only difference with DREOr is that this only gives Q so it is a bit faster

implement column pivoting to choose an stable orthogonal basis from a given set, which could be redundant, called "dictionary"

Usage: [Q] = DREOr(D, tol, ind);
 [Q] = DREOr(D);

Inputs:

D matrix the columns of which is a dictionary of normalized atoms
 tol tolerance set for considering as linearly dependent columns [default tol=1.0000e-7]
 ind (optional) indices determining the initial subspace
 [] can be used for tol and ind

Outputs:

Q orthonormal vectors spanning the same space as D, up to tolerance tol

References:

L. Rebollo-Neira, "Dictionary redundancy elimination", IEE Proceedings - Vision, Image and Signal Processing, Vol(151,1), 31-34 (2004).

See also DREOr DRE

5.2.9 FrDelete

deletes the requested vector from a given frame

It appropriately modifies the corresponding duals "beta", the updating depends on whether the vector "num" belongs to the remaining frame or not

Usage: [D,beta]=nfrdelete(D,beta,num);
 Usage: [D,beta]=nfrdelete(D,beta,num,ic);

Inputs:

D frame
 beta dual frame
 num index of the vector to be eliminated

ic = 1 if linearly independent (linearly dependent otherwise)

Outputs:

D reduced frame
beta updated dual frame (for the reduced D)

References:

L. Rebollo-Neira, ‘‘Constructive updating/downdating of oblique projectors: a generalization of the G
Vol(40), 6381-6394 (2007).

See <http://www.ncrg.aston.ac.uk/Projects/HNLApprox/> for more details

5.2.10 FrInsert

adds a vector to a frame. It also appropriately modifies the corresponding dual frame.

Usage: [D,beta]=nfrinsert(D,beta,atom,tol);

Inputs:

D frame
beta dual frame to D
atom new vector to be incorporated into the frame
tol tolerance (optional parameter) to decide linear dependence
default value = 1.0000e-7
dual if atom is linearly dependent dual is an arbitrary vector
default dual=atom

Outputs:

D updated frame
beta updated dual frame of D

References:

[1] L. Rebollo-Neira, ‘‘Constructive updating/downdating of oblique projectors: a generalization of t
Journal of Physics A: Mathematical and Theoretical}, Vol(40), 6381-6394 (2007)

This routine is equivalent to NBioInsert if the new atom is independent

see <http://www.ncrg.aston.ac.uk/Projects/HNLApprox/>

5.2.11 FrInsertBlock

adds vectors to a basis and gives the duals spanning the same space

Usage: [D,beta]=FrInsertBlock(D,beta,gb,tol);

Inputs:

D basis
gb new vectors to be incorporated into the basis
tol tolerance (optional parameter) to decide linear dependence
default value = 1.0000e-7

Outputs:

D updated basis
beta updated biorthogonal basis

or <http://www.ncrg.aston.ac.uk/Projects/HNLApprox/>

5.2.12 NBioDictIns

enlarges a basis selected from a given dictionary by one vector. It modifies the biorthogonal basis for the same space and gives the projection of the remaining atoms onto the orthogonal complementary space

Usage: `lambda = NBioDictIns(D, lambda, k);`

Inputs:

D dictionary, D(:,1-k-1) is the selected basis
lambda lambda(:,1:k-1)=biorthogonal functions to D(:,1:k-1)
lambda(:,k:end)=D(:,k:end) without component from D(:,1:k-1)
k k-th atom of D to incorporate it says that first k-1 atoms are already in basis

Outputs:

lambda lambda(:,1:k)=biorthogonal functions to D(:,1:k)
lambda(:,k+1:end)=D(:,k+1:end) without component from D(:,1:k)

References:

L. Rebollo-Neira, "Recursive bi-orthogonalisation approach and orthogonal projectors", math-ph/0209026 (2002).

Note: the difference between this routine and BioDictIns is that in this routine the orthonormal basis spanning D(:,1:k) is not available

See also BioDictIns, BioInsert, NBioInsert.

5.2.13 NBioInsert

adds an atom to a basis and modifies the biorthogonal basis for the same space

Usage: `[D, beta] = NBioInsert(D, beta, atom, tol);`

Inputs:

D already selected basis
beta biorthogonal functions to D
atom new atom to be incorporated into basis
tol tolerance (optional parameter) to decide linear dependence default value = 1.0000e-7

Outputs:

D updated basis
beta updated biorthogonal functions to D

References:

L. Rebollo-Neira, "Recursive bi-orthogonalisation approach and orthogonal projectors", math-ph/0209026 (2002).

See also BioInsert, NBioDictIns, BioDictIns.

Chapter 6

Examples

6.1 Example-Summary

<code>exa_ObliProj</code>	<code>using ObliProj</code>
<code>exa_OptObliProj</code>	<code>using OptObliProj</code>
<code>exa_RegObliProj</code>	<code>using RegObliProj</code>

6.2 Example-Description

6.2.1 `exa_ObliProj`

`using ObliProj`

Separates the components `f_v` in `V` from `f=f_v+f_w`; with `f_w` in `WC`.

6.2.2 `exa_OptObliProj`

`using OptObliProj`

Separates the component `fv` in `V` from `f=fv+fw`; with `fw` in `WC`.

6.2.3 `exa_RegObliProj`

`using RegObliProj`

Separates the component `fv` in `V` from `f=fv+fw`; with `fw` in `WC`.

Part III

Image Processing Tools

6.3 Function-Summary

CalcPSNR	returns the PSNR between the original image and its approximation
DCos	generates a matrix whos columns are discrete cosine vectors.
DetectLines	returns the index of vertical impulsive lines in an image
GenerateHats	Generates a hat dictionary
GenerateTrapezium	generates a vector representing a trapezium
ImageApproximation	Returns an approximation of an image generated by choosing atoms from dictionary using either thresholding or a greedy algorithm.
RemoveDependantAtoms	removes any dependant atoms from a given dictionary
TranslatePrototype	translates a vector to construct either a dictionary or a basis

6.4 Function-Description

6.4.1 CalcPSNR

returns the PSNR between the original image and its approximation

Calculates the Peak Signal to Noise Ratio (PSNR) between 2 matrices containing pixel intensity values.

Usage: `psnr = CalcPSNR(mImage1, mImage2);`

Inputs:

`mImage1` matrix of pixel intensity values representing the original image
`mImage2` matrix of pixel intensity values representing the approximated image
`maxIntensity` maximum allowed pixel intensity, default is 256 (8 bit image)

Outputs:

`psnr` the PSNR resulting from the approximation

6.4.2 DCos

generates a matrix whos columns are discrete cosine vectors.

Returns discrete cosine vectors that belong to the Euclidean space of size `szSpace`. The default is to return a basis for the space.

Usage `mCosines = DCos(szSpace, nFrequencies, redundancy);`
`mCosines = DCos(szSpace, nFrequencies);`
`mCosines = DCos(szSpace);`

Inputs:

`szSpace` the size of the Euclidean space the vectors should belong to
`nFrequencies` number of frequencies to use starting from 0. If not specified will be the same as the size of the space
`redundancy` redundancy of the dictionary, the default is 1 (basis)

Outputs:

`mCosines` matrix whos columns are discrete cosine vectors.

6.4.3 DetectLines

returns the index of vertical impulsive lines in an image

Searches a matrix representing the pixel intensities of an image for columns where all the values are equal to `lineValue`. Note this will also return the index of vertical

edges.

Usage: `iLine = DetectLines(mImage, lineValue);`
 `iLine = DetectLines(mImage);`

Inputs:
 `mImage` double matrix representing image pixel intensities
 `lineValue` value to search for default is 0.

Outputs:
 `iLine` vector containing the index's of the columns of `mImage` containing vertical lines

6.4.4 GenerateHats

Generates a hat dictionary

Builds a dictionary for a space of size `szSpace` from one or more hat dictionaries or basis, where the length of there support is given in the vectot hats.

Usage: `mHatDictionary = GenerateHats(hats, szSpace, dictionary);`

Inputs:
 `hats` vector of support lengths for each dictionary
 `szSpace` number of discrete points in each atom
 `dictionary` set to 0 if the dictionary is composed from several hat basis, or 1 if it is composed from several hat dictionaries

Outputs:
 `mHatDictionary` matrix whose columns are the atoms fromt he hat dictionaries

6.4.5 GenerateTrapezium

generates a vector representing a trapezium

Generates a discrete vector of points representing the vertical distance between the base of an isosceles trapezium and the other three sides. You choose the length of the trapeziums base, this will 2 less than the size of `vTrapezium` as the base values are zero. You also choose the length of the trapeziums top.

Usage: `vTrapezium = GenerateTrapezium(lBase, lTop);`
 `vTrapezium = GenerateTrapezium(lBase);`

Inputs:
 `lBase` number of discrete points for the trapeziums base
 `lTop` number of discrete points for the trapeziums top, the default is 1

Outputs:
 `vTrapezium` column vector of points representing the vertical distance between the base of an isosceles trapezium and the other three sides.

See also `TranslatePrototype`

6.4.6 ImageApproximation

Returns an approximation of an image generated by choosing atoms from dictionary using either thresholding or a greedy algorithm.

Usage: `[mImageApprox, mNCn, mCn, mICn, actualPSNR, processingTime, ...
mError] = ImageApproximation(mImage, mAtoms, algorithm, ...
criteria, blockWidth);`

Inputs:

- `mImage` the matrix of pixel intensity values
- `mAtoms` matrix whos columns are the atoms from the dictionary we use to approximate the image with
- `algorithm` name of the algorithm to use
- `criteria` the target psnr between the original image and its approximation if using a greedy algorithm or the threshold if using Thresholding
- `blockWidth` width of the square blocks that the image will be processed in

Outputs:

- `mImageApprox` matrix representing the approximated image
- `mNCn` matrix containing the number of coefficients used to represent each block of the image
- `mICn` array containing the index's of the retained coefficients
- `actualPSNR` psnr between the original image and its approximation
- `processingTime` time in seconds to process the image
- `mError` matrix containing the norm of the error between the original image and the approximated image for each block processed.

6.4.7 RemoveDependantAtoms

removes any dependant atoms from a given dictionary

Normalises the dictioanry and then removes any atoms that have an inner product of within tol of 1.

Usage: `[mUniqueDictionary iRemovedAtoms] = RemoveDependantAtoms(...
mDictionary, tol);`
`[mUniqueDictionary iRemovedAtoms] = RemoveDependantAtoms(...
mDictionary);`

Inputs:

- `mDictionary` dictionary of atoms
- `tol` tolerance of how similar atoms can be, default is 1e-13

Outputs:

- `mUniqueDictionary` dictionary with dependant atoms removed
- `iRemovedAtoms` index of the dependant atoms

6.4.8 TranslatePrototype

translates a vector to construct either a dictionary or a basis

Constructs a matrix whos columns are vectors forming either a redundant dictionary or a basis for the Euclidean space of dimension szSpace. Each vector is generated by translating one point at a time the discrete values contained in vPrototype, i.e.

```
szSpace = 3;
vPrototype = [ 1 ];
mVectors = [ 1 0 0;
            0 1 0;
            0 0 1 ];
```

If dictionary is not specified or set to 1 we apply the 'cut off' approach to create a dictionary for the space i.e.

```
dictionary = 1;
szSpace = 3;
vPrototype = [ 1 1];
mVectors = [ 1 0 0;
             1 1 0;
             0 1 1;
             0 0 1 ]
```

If dictionary is set to 0 we adopt cyclic boundry conditions to create a basis for the space, i.e.

```
dictionary = 0;
szSpace = 3;
vPrototype = [ 1 1];
mVectors = [ 1 1 0;
             0 1 1;
             1 0 1 ];
```

Usage: mVectors = TranslatePrototype(vPrototype, szSpace, dictionary);
 mVectors = TranslatePrototype(vPrototype, szSpace);

Inputs:

vPrototype vector representing the shape to be translated.
szSpace size of the Euclidean space we want to span.
dictionary 0 to generate a basis and 1 to generate a redundant dictionary for the space, the default is to generate a dictionary.

Outputs:

mVectors matrix whos columns span the space of dimension szSpace

See also GenerateTrapezium

6.5 Examples

6.6 Example-Summary

exa_image_approximation	approximating an image using OMP
exa_impulse_removal	Elimination of random lines from an image using the function OOMP-FinalRefi()

6.7 Example-Description

6.7.1 exa_image_approximation

approximating an image using OMP

Example of using the OMP algorithm to approximate the image of Lena using a dictionary comprised from a deiscrete cosine redundancy 2 dictionary and hat dictionaries of support 1, 3 and 5.

6.7.2 exa_impulse_removal

Elimination of random lines from an image using the function OOMPFinalRefi()

Removes random vertical lines from an image by projecting onto atoms chosen from a

spline wavelets dictionary using OOMPFinalRefi().
Construct the Spline Wavelet Dictionary

Part IV

Spline Dictionaries

Chapter 7

Uniform

7.1 Function-Summary

BSpline	gives the analytical form of k-th B-spline of order m on l-th subinterval of given partition t
DictSpline	generates dictionary of cardinal B-spline functions of order m
Differ	calculates (s-1)-th divided difference of $\max((t-x)^{m-1}, 0)$ where s is the number of knots in sequence t (i.e., s=length(t))
ErrorTest	tests orthogonality of a sequence or biorthogonality of two sequences.
Green	calculates $(x_+)^m = x^m$ for $x \geq 0$ (it is 0 for $x < 0$). This functions is known as truncated powers.
NormDict	normalizes a given dictionary
SplineLevel	generates a B-spline dictionary depending on given parameters
SymSpline	gives the analytical form of B-spline of order m with knots in partition t
TSpline	generates B-spline basis of order m corresponding to knot sequence t

7.2 Function-Description

7.2.1 BSpline

gives the analytical form of k-th B-spline of order m on l-th subinterval of given partition t

Usage: `f = BSpline(m, k, l, t);`
`f = BSpline(m, k, l);`

Inputs:

m order of spline ($m \geq 1$), $m=1$ is a piecewise constant function
k specifies the index of spline, B-spline living on on $I=[t(k),t(k+m)]$ is calculated if the sequence of knots t is not defined then $I=t(k:k+m)=[k-1,k-1+m]$
l specifies the interval $[t(1),t(1+1)]$ on which the k-th B-spline is studied
t sequence of knots (optional)
if t is a single number then the sequence is considered to be $t:t+m$
if t not specified then $t=k-1:k-1+m$

Output:

f analytical form of k-th B-spline of order m on l-th subinterval of t

References:

L.L. Schumaker, Spline Functions: Basic Theory, New York, Wiley, 1981.

Remark: It is not recommended to use this procedure by user. You can do the same using SymSpline.

7.2.2 DictSpline

generates dictionary of cardinal B-spline functions of order m

Usage: `D = DictSpline(m, L, sp, b1, b2, type);`

Inputs:

m order of spline functions ($m \geq 1$), $m=1$ is a piecewise constant function
L number of discrete points
sp vector [sp(1),sp(2)] specifying the interval
b1 coarser partition of sp, points $sp(1)+k*b1$, $k=0$
b2 finer partition of sp, points $sp(1)+k*b2$, $k=0$
type either ESEP or EPKB

Output:

D dictionary of cardinal B-spline functions of order

Remark: This procedure uses the translation property of inner cardinal B-splines. It calls the routine SplineLevel to do the job.

7.2.3 Differ

calculates (s-1)-th divided difference of $\max((t-x)^{(m-1)}, 0)$ where s is the number of knots in sequence t (i.e., $s=\text{length}(t)$)

Usage: `f = Differ(x, t, m);`

Inputs:

x discrete variable
t knot sequence
m order

Output:

f (s-1)-th divided difference of $\max((t-x)^{(m-1)}, 0)$

Remark: Sequence t must be ordered.

7.2.4 ErrorTest

tests orthogonality of a sequence or biorthogonality of two sequences.

Usage: `errortest(D, beta);`
`errortest(Q);`

Inputs:

D sequence of vectors
beta (optional) biorthogonal sequence

Output:

f orthogonality of D or biorthogonality D w.r.t beta

7.2.5 Green

calculates $(x_+)^m = x^m$ for $x \geq 0$ (it is 0 for $x < 0$). This functions is known as truncated powers.

Usage: `f = Green(x, m);`

Inputs:

`x` discrete variable
`m` order

Output:

`f` $(x_+)^m$ (see definition of this above)

References:

L.L. Schumaker, *Spline Functions: Basic Theory*, New York-Wiley, 1981.

7.2.6 NormDict

normalizes a given dictionary

Usage: `D = NormDict(D, delta);`
`D = NormDict(D);`

Inputs:

`D` non-normalized dictionary
`delta` parameter, the discrete norm of `D` is multiplied by `sqrt(delta)`
(default value is 1)

Outputs:

`D` normalized dictionary

Remark: It normalizes the columns of matrix `D`.

7.2.7 SplineLevel

generates a B-spline dictionary depending on given parameters

Usage: `D = SplineLevel(m, x, b1, b2, type);`

Inputs:

`m` order of splines
`x` discrete variable
`b1` coarser partition of `sp`, points `sp(1)+k*b1`, `k=0`
`b2` finer partition of `sp`, points `sp(1)+k*b2`, `k=0`
`type` either ESEP or EPKB

Output:

`D` dictionary of spline functions

References:

M. Andrlé and L. Rebollo-Neira, "Cardinal B-spline dictionaries on a compact interval", *Applied and Computational Harmonic Analysis*, Vol(18,3), 336-346 (2005).

7.2.8 SymSpline

gives the analytical form of B-spline of order `m` with knots in partition `t`

Usage: `[f, p] = SymSpline(m, t);`
`[f, p] = SymSpline(m);`

Inputs:

`m` order of spline (`m`>=1), `m=1` is a piecewise constant function
`t` sequence of knots (optional)

if t is a single number then the sequence is considered to be t:t+m
if t not specified, t=0:m

Outputs:

f array of m symbolical polynomials, each polynomial describes the desired B-spline on the subinterval $[t(i),t(i+1)]$, $i=1,\dots,m$
p matrix of coefficients for polynomials expressed in f, each row in this matrix represents a_{m-1}, \dots, a_0 for polynomials written as $a_{m-1}x^{m-1}+\dots+a_0$

Remark: If length of t is bigger than m+1, this procedure takes in account only first m+1 knots of t

References:

L.L. Schumaker, Spline Functions: Basic Theory, New York, Wiley, 1981.

7.2.9 TSpline

generates B-spline basis of order m corresponding to knot sequence t

Usage: D = TSpline(x, t, m);

Inputs:

x variable range (discrete points)
t knot sequence (could be multiple knots)
m order of splines (m=1 means a piecewise constant functions)

Output:

D B-spline function basis corresponding to knot sequence t

Remark: The sequence t is sorted before calculation.

References:

L.L. Schumaker, Spline Functions: Basic Theory, New York, Wiley, 1981.

Chapter 8

Non Uniform

8.1 Function-Summary

CutDic	produces a non-uniform B spline dictionary
NonBSpline	Computes the value of B spline basis at x0 by the recurrence formula for the non-uniform B spline.
NonUniB	computes all non-uniform B spline over the partition 'p'
ProducePartition	using the curvature of the signal f, it compute the knots of a partition

8.2 Function-Description

8.2.1 CutDic

produces a non-uniform B spline dictionary

Usage: `D = CutDic(partition, m, L, level);`

Inputs:

`partition` a partition to produce a non-uniform B spline dictionary (it can be computed by the function 'producepartition')

`m` the order of the spline

`L` the number of the sampling of the functions

`level` it is related with the width of the B spline basis. When level=1, the function outputs the B spline basis.

Outputs:

`D` the non-uniform B spline dictionary (matrix)

8.2.2 NonBSpline

Computes the value of B spline basis at x0 by the recurrence formula for the non-uniform B spline.

Usage: `re = NonBSpline(m, t, x0);`

Inputs:

`m` the order of splines

`t` the partition (the number of entris in t is m+1)

`x0` the point for computing

Outputs:

`re` the value of B spline at x0

8.2.3 NonUniB

computes all non-uniform B spline over the partition 'p'

Usage: `D = NonUniB(a, b, m, p, L);`

Inputs:

`a,b` the end points of the interval
`m` the order of the spline
`p` the partition
`L` the number of the sampling of the functions

Outputs:

`D` the non-uniform B spline over the partition p (matrix, `D(:,j)` denotes jth B spline basis)

8.2.4 ProducePartition

using the curvature of the signal f, it compute the knots of a partition

Usage: `partition = ProducePartition(a, b, f, cut);`

Inputs:

`a,b` the end points of the interval
`f` signal
`cut` sub-divided level of the partition.

Outputs:

`partition` the knots of the partition. The first entry is a and the last one is b

Chapter 9

Wavelets

9.1 Function-Summary

BuildDict	helps you to construct a multiresolution-like spline wavelet dictionary or a B-spline dictionary
ElimBound	eliminates redundant boundary wavelets to have a basis for the cut-off spline wavelet dictionary constructed with $b=1$
GDictFast	generates dictionaries by translating prototype functions
NumFun	states how many functions $f(a^j * x - b * k)$, where k is an integer, have non-trivial intersection with the interval $[c, d]$
SPL	generates B-splines of order m at scale j with translation parameter k , $B(a^j * x - k)$. Multiple knots for construction boundary functions are considered.
STPoint	returns such a translation parameter k that $f(a^j * x - b * k)$ is the first function having non-trivial intersection with the point c
ScalLevel	generates a set of all translated B-splines, $B(a^j * x - b * k)$, having non-trivial intersection with the given interval. It can be also used for construction (Chui) cubic B-spline basis (for $b = 1$ only).
SplineChuiWav	generates the Chui semi-orthogonal cubic spline wavelet, $w(a^j * x - k)$ on the given interval.
SplineScal	generates dilated/translated B-spline, $B(a^j * x - b * k)$, of order m on the given interval.
SplineWavelet	generates semi-orthogonal spline wavelet, $w(a^j * x - b * k)$, of order 1, 2 or 4 on the given interval
WavLevel	generates a set of all translated spline wavelets, $w(a^j * x - b * k)$, having non-trivial intersection with the given interval. It can be also used for construction (Chui) cubic B-spline wavelet basis (for $b = 1$ only).

9.2 Function-Description

9.2.1 BuildDict

helps you to construct a multiresolution-like spline wavelet dictionary or a B-spline dictionary

To create a dictionary of your choice, edit this file and set the desired values of the variables.

Available multiresolution-like dictionaries are:

```
name='1'           Haar dictionary (cut-off construction)
   ='2'           linear dictionary (cut-off construction)
```


'4' cubic dictionary (cut-off construction)
'chui_cubic' cubic spline wavelet basis (multiple knots)

Available B-spline dictionaries are:

name='1b' piece-wise constant B-spline dictionary
'2b' linear B-spline dictionary (cut-off construction)
'4b' cubic B-spline dictionary (cut-off construction)
'Nb' B-spline dictionary of order N (any positive integer)
'chui_cubicb' cubic B-spline dictionary (multiple knots)

Description of other parameters

a dilation factor (positive integer)
b translation factor (b=1 for basis, keep 1/b being integer)
use b=1 only for 'chui_cubic' and 'chui_cubicb'
sp array sp=[c,d] stands for interval [c,d]
j array containing all the scales to be considered
note that larger 'j' implies finer scale
L number of points partitioning the interval sp=[sp(1) sp(2)]
it must be a positive integer value satisfying
 $L = J * (sp(2) - sp(1)) / (b * (a^{-j_{max}})) + 1$ where jmax stands for the
finest scale to be considered and J is a positive integer

Outputs:

x dicretization of the interval sp containing L nodes
D desired dictionary
ind array of indices separating different scales in D

EXAMPLE:

The following example constructs a cubic multiresolution-like wavelet dictionary D on the interval [0,8] with scale factor a=2, b=0.5, j=[0:4] The interval [0,8] will be partitioned into L=2049 points.

```
name='4';b=0.5;a=2;  
sp=[0 8];  
j=[0:4];  
L=2049;  
[D, ind] =gdicfast(name,{L;sp;j;a;b});
```

Comments:

For B-spline dictionaries see also TestSpline
For a cut-off multiresolution-like wavelet basis see ElimBound

References:

M. Andrle and L. Rebollo-Neira, "Spline wavelet dictionaries for non-linear signal approximation", preprint, 2005.
M. Andrle and L. Rebollo-Neira, "Cardinal B-spline dictionaries on a compact interval", Applied and Computational Harmonic Analysis, Vol(18,3), 336-346 (2005).
C.K. Chui and E. Quak, "Wavelets on a Bounded Interval", in Numerical Methods of Approximation Theory, Vol. 9 (Eds. D. Braess and L.L. Schumaker), pp. 53-75, Birkhauser, Basel, 1992.

9.2.2 ElimBound

eliminates redundant boundary wavelets to have a basis for the cut-off spline wavelet dictionary constructed with $b=1$

Usage: [DD, ind] = ElimBound(m, D, ind);

Inputs:

m order of splines in dictionary (positive integer)
D dictionary
ind array of final indices for every scale in D (optional)

Outputs:

DD basis, D without the redundant boundary wavelets
ind updated indices for DD

For the construction of cut-off multiresolution-like wavelet dictionaries see BuildDict.

Note: The first scale is assumed to contain scaling functions thus the redundant wavelets are removed from all scales except the first one.

If ind is not specified it considers only one scale (wavelets) and $m-1$ functions are removed from both sides.

Comments: The support of semi-orthogonal spline wavelet of order m is given by $\text{supp}=2*m-1$. Thus the number of functions to eliminate at every scale at each border is $n=(\text{supp}-1)/2=m-1$.

References:

M. Andrlé and L. Rebollo-Neira, "Spline wavelet dictionaries for non-linear signal approximation", preprint, 2005.

9.2.3 GDictFast

generates dictionaries by translating prototype functions

Usage: D = GDictFast(name, pars);

Inputs:

name type of dictionary (string format)
pars parameters (cell format)
pars = {L,sp,j,a,b}

Description of the parameters

L number of points partitioning the interval $\text{sp}=[\text{sp}(1) \text{sp}(2)]$
sp array $\text{sp}=[c \ d]$ stands for interval $[c,d]$
j array containing all the scales to be considered note that larger j implies finer scale
a dilation factor (positive integer)
b translation factor ($b=1$ for basis, keep $1/b$ being integer) for 'chui_cubic' and 'chui_cubicb' use $b=1$ only

Outputs:

D desired dictionary
ind array of indices separating different scales in D

Comments:

The dictionaries are constructed in the following way: a prototype function for every scale is computed for values $x=\text{linspace}(\text{sp}(1),\text{sp}(2),L)$ (x is a discretization of the

interval sp containing L nodes). Then this prototype function is shifted on x by an appropriate number of nodes. For this end $(L-1)*(b*a^{-j_{max}})/(sp(2)-sp(1))$ must be an integer where j_{max} stands for the finest scale parameter. In the case of 'chui_cubic' or 'chui_cubicb' dictionaries only the inner functions are constructed by the method above. The boundary function are calculated using given analytical expressions.

Only scales with at least one inner function are considered.

References:

- M. Andrle and L. Rebollo-Neira, "Spline wavelet dictionaries for non-linear signal approximation", preprint, 2005.
- M. Andrle and L. Rebollo-Neira, "Cardinal B-spline dictionaries on a compact interval", Applied and Computational Harmonic Analysis, Vol(18,3) 336-346 (2005).

9.2.4 NumFun

states how many functions $f(a^j * x - b * k)$, where k is an integer, have non-trivial intersection with the interval $[c, d]$

Usage: `n = NumFun(name, type, c, d, j, a, b);`

Inputs:

name order of splines (positive integer) or 'chui_cubic' (string)
 type string, 'scal.f.' for scaling functions, 'wavelet' for wavelets
 c,d the given interval [c,d]
 j scale level (a^j is the dilation)
 a scaling factor
 b translation factor

Output:

n the number of consecutive translates $f(a^j * x - b * k)$ having non-trivial intersection with the interval $[c, d]$

9.2.5 SPL

generates B-splines of order m at scale j with translation parameter k , $B(a^j * x - k)$. Multiple knots for construction boundary functions are considered.

Usage: `f = SPL(x, m, j, k, a);`

Inputs:

x a discretization of the given interval
 j scale level (a^j is the dilation)
 m order of splines
 k translation parameter
 a scale factor

Output:

f B-splines of order m at scale j with translation parameter k

Note:

The interval $[x(1) \ x(end)]$ must be $[0, K]$ type where K is an integer

9.2.6 STPoint

returns such a translation parameter k that $f(a^j * x - b * k)$ is the first function having non-trivial intersection with the point c

Usage: `k = STPoint(name, type, c, j, a, b);`

Inputs:

name order of splines (positive integer) or 'chui_cubic' (string)
type string, 'scal.f.' for scaling functions, 'wavelet' for wavelets
c left point of the given interval
j scale level (a^j is the dilation)
a scaling factor
b translation factor

Output:

k desired translation parameter such that $f(a^j*x-b*k)$ is the first function having non-trivial intersection with the point c

9.2.7 ScalLevel

generates a set of all translated B-splines, $B(a^j*x-b*k)$, having non-trivial intersection with the given interval. It can be also used for construction (Chui) cubic B-spline basis (for $b = 1$ only).

Usage: `D = ScalLevel(name, x, j, a, b)`

Inputs:

name specifies the type of splines
x a discretization of the given interval
j scale level (a^j is the dilation)
a scaling factor
b translation factor

Available B-splines are:

name=1 piece-wise constant B-spline dictionary
=2 linear B-spline dictionary (cut-off construction)
=4 cubic B-spline dictionary (cut-off construction)
=N B-spline dictionary of order N (any positive integer)
='chui_cubic' cubic B-spline dictionary (multiple knots)

Output:

D set of B-splines at scale j having non-trivial intersection with the given interval

9.2.8 SplineChuiWav

generates the Chui semi-orthogonal cubic spline wavelet, $w(a^j*x-k)$ on the given interval.

Usage: `w = SplineChuiWav(x, j, k, a);`

Inputs:

x a discretization of the given interval
j scale level (a^j is the dilation)
k translation parameter
a scale factor

Output:

w normalized cubic Chui semi-orthogonal spline wavelet

References:

C.K. Chui and E. Quak, "Wavelets on a Bounded Interval", in Numerical Methods of Approximation Theory, Vol. 9 (Eds. D. Braess and L.L. Schumaker), pp. 53-75, Birkhauser, Basel, 1992.

9.2.9 SplineScal

generates dilated/translated B-spline, $B(a^j * x - b * k)$, of order m on the given interval.

Usage: `w = SplineScal(x, j, k, m, a, b`

Inputs:

`x` a discretization of the given interval
`j,k` dilation and translation parameters
`a` scaling factor
`b` translation factor
`m` order of spline (positive integer)

Output:

`w` dilated/translated B-spline of a given order

9.2.10 SplineWavelet

generates semi-orthogonal spline wavelet, $w(a^j * x - b * k)$, of order 1, 2 or 4 on the given interval

Usage: `w = SplineWavelet(x, j, k, m, a, b);`

Inputs:

`x` a discretization of the given interval
`j,k` dilation and translation parameters
`a` scaling factor
`b` translation factor
`m` order of spline wavelet (1,2 or 4)

Output:

`w` normalized dilated/translated spline wavelet of a given order

9.2.11 WavLevel

generates a set of all translated spline wavelets, $w(a^j * x - b * k)$, having non-trivial intersection with the given interval. It can be also used for construction (Chui) cubic B-spline wavelet basis (for $b = 1$ only).

Usage: `D = WavLevel(name, x, j, a, b);`

Inputs:

`name` specifies the type of spline wavelets
`x` a discretization of the given interval
`j` scale level (a^j is the dilation)
`a` scaling factor
`b` translation factor

Available types of spline wavelets:

`name=1` Haar dictionary (cut-off construction)
`=2` linear dictionary (cut-off construction)
`=4` cubic dictionary (cut-off construction)
`= 'chui_cubic'` cubic spline wavelet basis (multiple knots)

Output:

`D` set of all normalized spline wavelets at scale level j having non-trivial intersection with the given interval