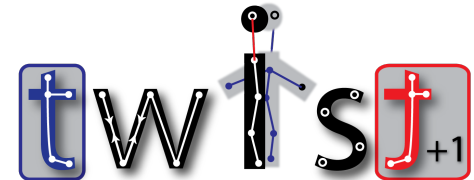


Nonlinear Approximation of Spatiotemporal Data Using Diffusion Wavelets

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ACV Kolloquium
PRIP, TU Wien, April 20, 2007



Motivation of this talk

- **Wavelet based methods:**

proven to be successful in signal and image analysis

main applications: edge-preserving smoothing and denoising of functions in $L^2(\mathbb{R}^n)$, $n \in \mathbb{N}$

- Recent concept of **diffusion wavelets** (Coifman et al.):

construction of wavelet bases for functions defined on other than \mathbb{R}^n , such as certain domains, manifolds and **graphs**.

- **In this talk:** study the use of classical wavelet algorithms in a graph based setting:

Input data: an image sequence, regarded as $2d + 1$ time data set

Model: the whole image sequence as a weighted graph

Output: Compressed data set, structure-preserving smoothing

Further goal: Spatiotemporal segmentation via diffusion wavelets

Outline of this talk

1. Wavelets and Multiresolution Analysis on \mathbb{R}
 - (a) Orthonormal Wavelet Bases
 - (b) Nonlinear Wavelet Approximation
2. Wavelet Analysis on a Graph
3. Nonlinear Approximation of Spatiotemporal Data Using Diffusion Wavelets
4. Conclusion and Outlook Towards Spatiotemporal Segmentation

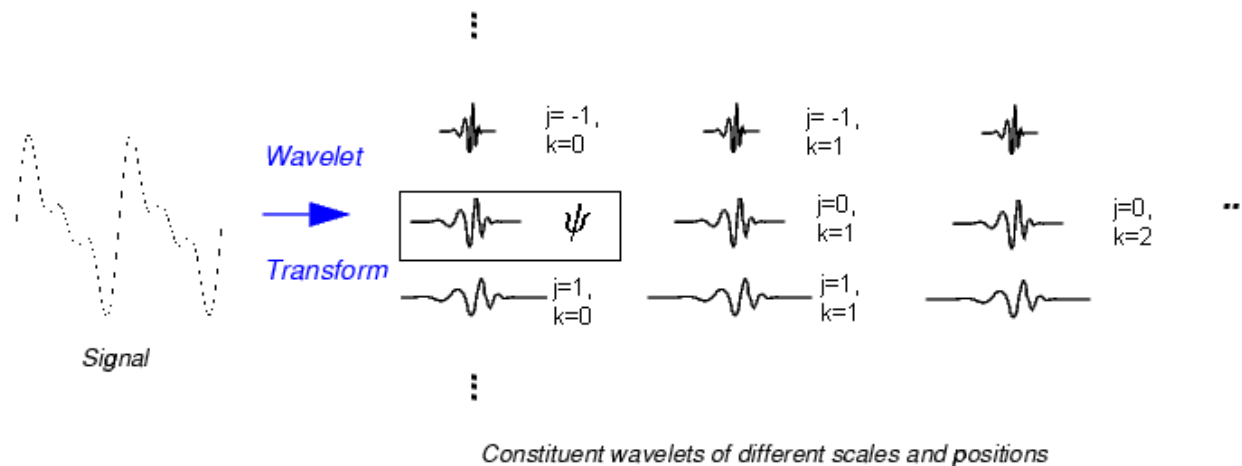
1. Wavelets and Multiresolution Analysis on \mathbb{R}

(a) Orthonormal Wavelet Bases

- Wavelet transform:

Decomposition of a function (1d signal or 2d image) into a series constituent of localized waves $(\psi_{j,l})_{j,l \in \mathbb{Z}}$

$f = \sum_{j,k \in \mathbb{Z}} \langle f, \psi_{j,l} \rangle \psi_{j,l}$, where $\psi_{j,l}$ are dilated (squeezed/stretched) and translated versions of a mother wavelet $\psi \in L^2(\mathbb{R})$.



In applications:

Calculation of coefficients via fast wavelet transform, using a cascade of filters

$$f \xrightarrow{\text{FWT}} (d_{j,k})_{j,k \in \mathbb{Z}},$$

$$\begin{array}{ccccccccccc} f = a_0 & \rightarrow & a_1 & \rightarrow & a_2 & \rightarrow & \dots & \rightarrow & a_{j-1} & \rightarrow & a_j \\ & & \searrow & & \searrow & & & & \searrow & & \searrow \\ & & d_1 & & d_2 & & & & d_{j-1} & & d_j \end{array}$$

where each horizontal arrow represents the same filtering and subsampling step $a_{j+1} = \downarrow_2 (a_j * g)$, and similarly, $d_{j+1} = \downarrow_2 (a_j * h)$, g, h CMF.

$(a_{j,l})_l$ approximation coefficients at scale (resolution) j ,
 $(d_{j,l})_l = (\langle f, \psi_{j,l} \rangle)_l$ **wavelet coefficients** at scale j .

(a) Nonlinear Wavelet Approximation

$(\psi_{j,l})_{j \geq 1, l \in \mathbb{Z}}$ ONB \implies for $f \in L^2(\mathbb{R})$,

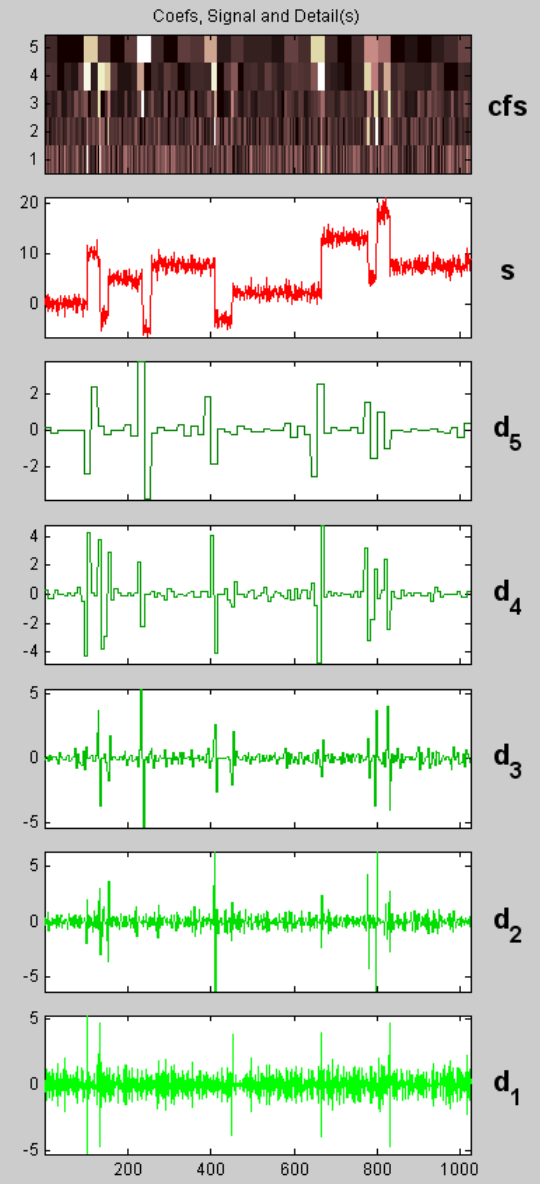
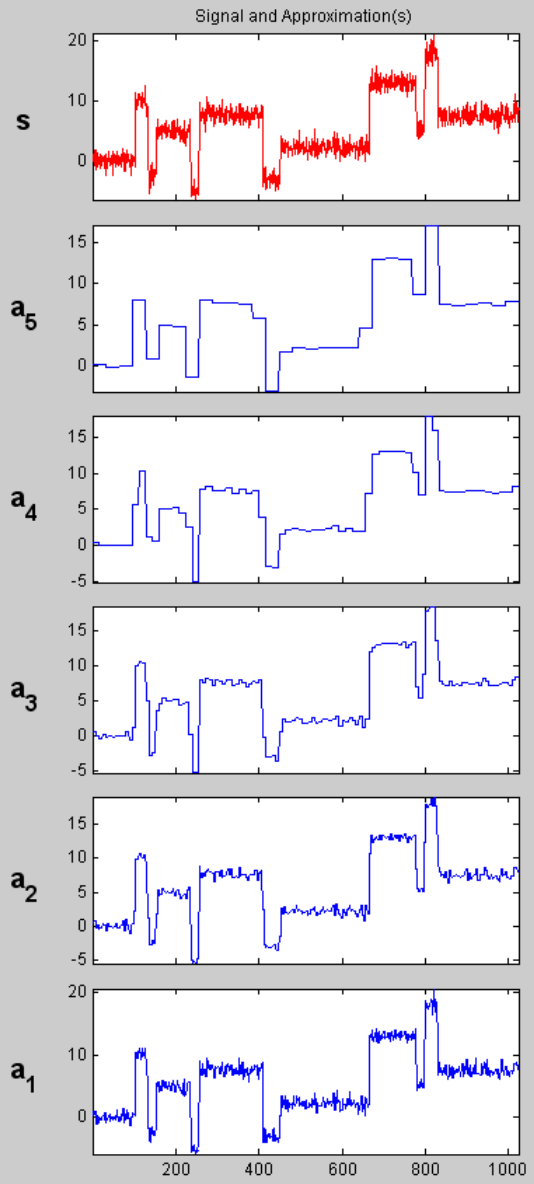
$$\|f\|_{L^2(\mathbb{R})}^2 = \sum_{j,l} |\langle f, \psi_{j,l} \rangle|^2.$$

\implies all the information of f maintained in the sequence of coefficients, **salient information** is reflected in the **largest coefficients**

\implies efficient approximation using only the N largest coefficients for reconstruction, realized by **thresholding** on the coefficients

\implies discontinuity preserving smoothing,

large theory relating the error of approximation to the function's properties



Data (Size)

Wavelet

Level

Analyze

Statistics

Compress

Histograms

De-noise

Display mode :

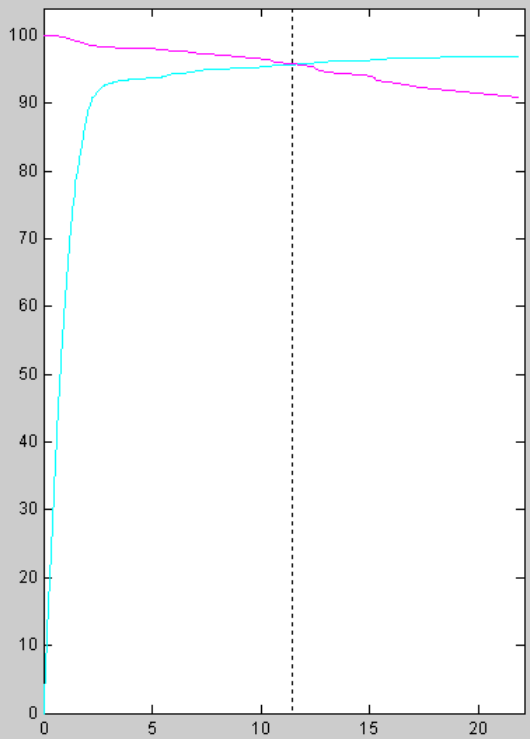
More Display Options

Colormap

Nb. Colors

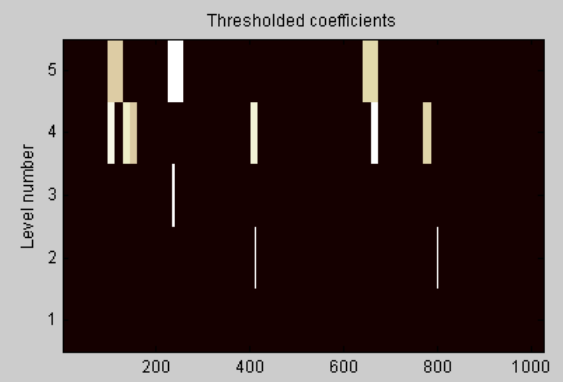
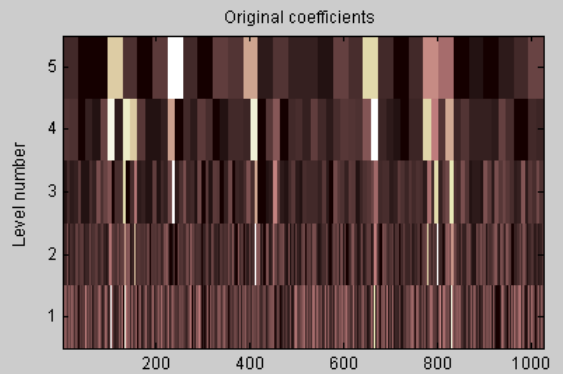
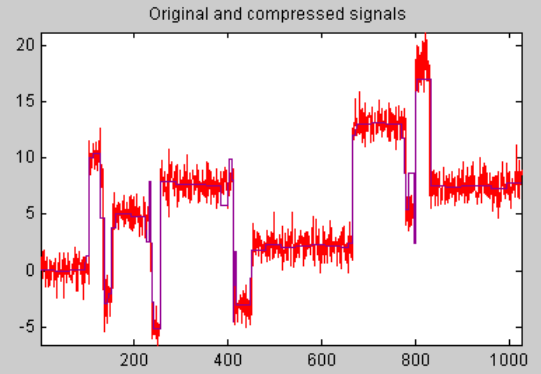
Close

Navigation and control buttons: X+, Y+, XY+, X-, Y-, XY-, Center On, X, Y, Info, X=, Y=, History, View Axes



----- Global threshold
 --- Retained energy in %
 --- Number of zeros in %

Retained energy 95.84 % -- Zeros 95.70 %



Data (Size)
 Wavelet
 Level

Global thresholding

Select thresholding method

 Select Global Threshold

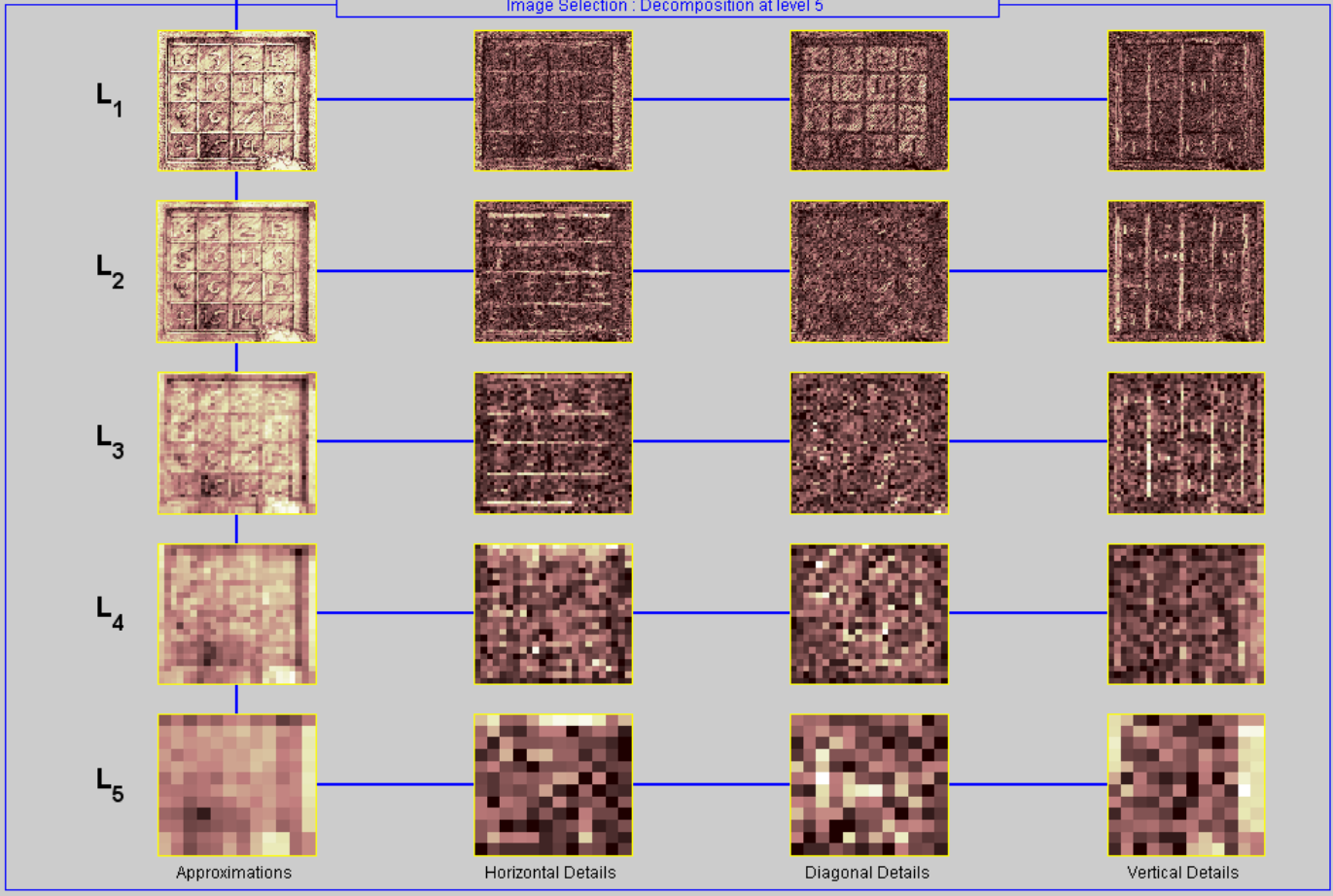
 Retained energy %
 Number of zeros %

Colormap
 Nb. Colors

Navigation and info controls: X+, Y+, XY+, X-, Y-, XY-, Center On, X, Y, Info, X=, Y=, History, View Axes



Image Selection : Decomposition at level 5



Data (Size) detail (359x371)
Wavelet sym 4
Level 5

Analyze

Statistics

Compress

Histograms

De-noise

Decomposition at level : 5

View mode : Tree

Full Size 1 2 3

Operations on selected image :

Visualize

Full Size

Reconstruct

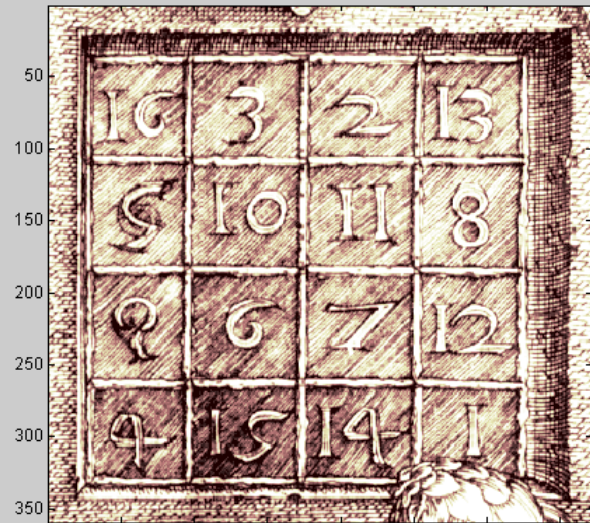
Colormap pink
Nb. Colors 64
Brightness - +

Close

Navigation and information controls including X+, Y+, XY+, X-, Y-, XY-, Center On, X, Y, Info, X=, Y=, History, View Axes.

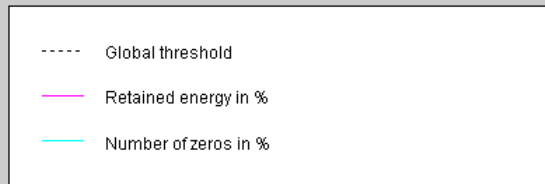
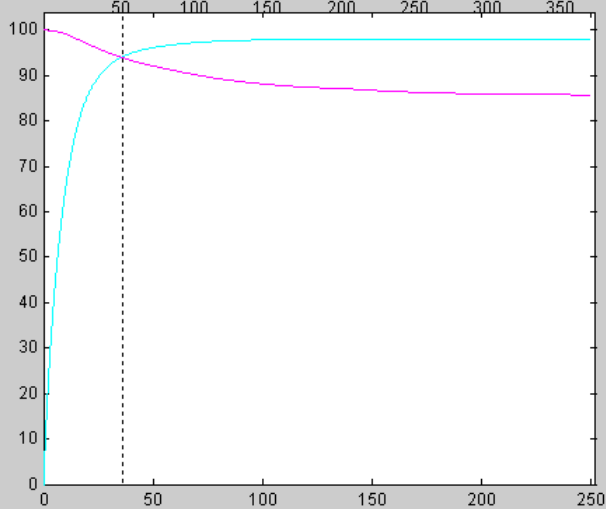
detail (359 x 371) analyzed at level 3 with sym4

Original image



Retained energy 94.04 % -- Zeros 94.04 %

Compressed image



Data (Size)
Wavelet
Level

Global thresholding

Select thresholding method

Select Global Threshold

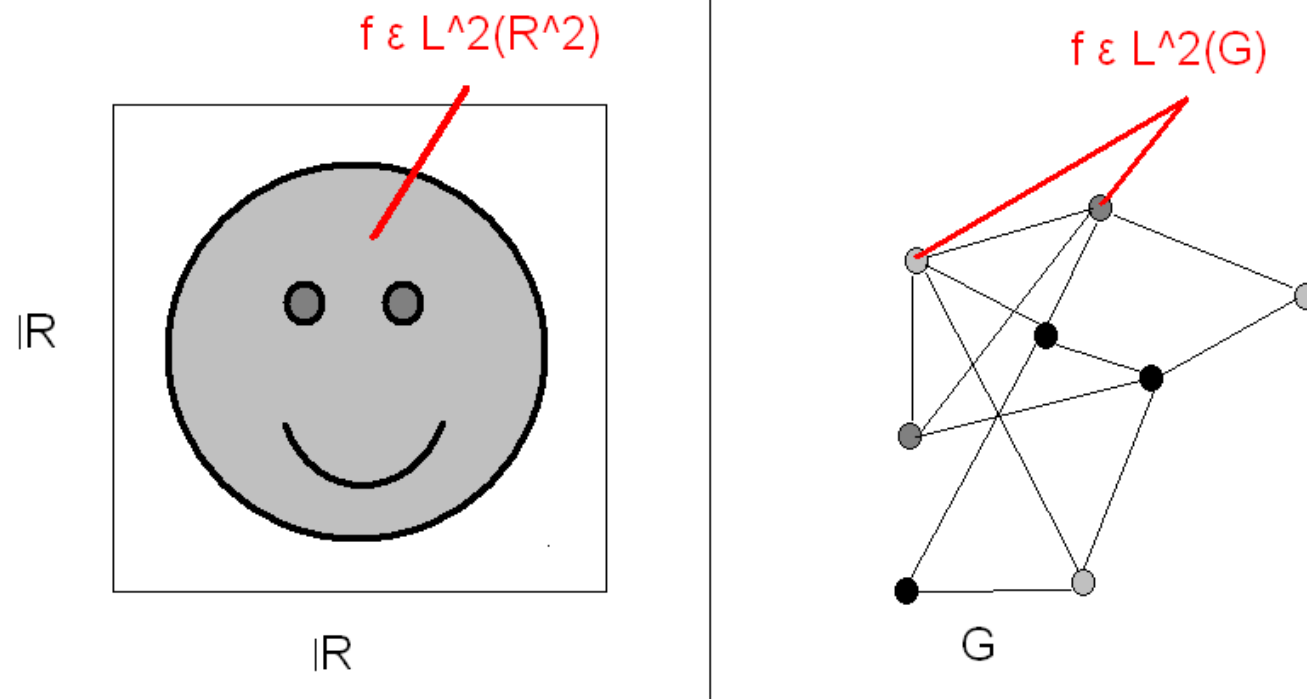
Retained energy %
Number of zeros %

Colormap
Nb. Colors
Brightness

X+ Y+ XY+ Center On X Y Info X= Y= History < > << >> View Axes

2. Wavelet Analysis on a Graph

- How to extend wavelet analysis on a graph?:

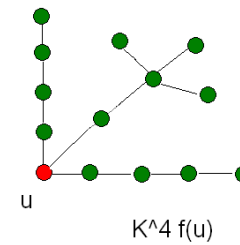
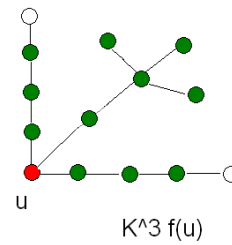
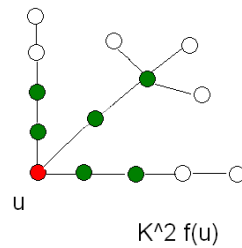
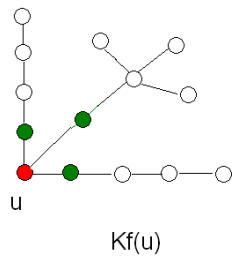


Dilations (stretching and squeezing) like on \mathbb{R} cannot be used for scaling
 \Rightarrow use **spectral methods** to define a multiresolution analysis

Diffusion operator K :

averaging operator acting on functions f on G :

$$Kf(u) = \frac{1}{\sqrt{d_u}} \sum_{v, v \sim u} \left(\frac{f(v)}{\sqrt{d_v}} - \frac{f(u)}{\sqrt{d_u}} \right) W(u, v)$$



Diffusion Wavelets

R.R.COIFMAN, S. LAFON, A.B. LEE, M. MAGGIONI, B. NADLER, F. WARNER AND S.W. ZUCKER: **GEOMETRIC DIFFUSIONS AS A TOOL FOR HARMONIC ANALYSIS AND STRUCTURE DEFINITION OF DATA**, PROC. NAT. AC. OF SC., VOL 102(21), MAY 2005
R.R. COIFMAN, M. MAGGIONI: **DIFFUSION WAVELETS**, ACHA, VOL. 21(1), JULY 2006

Diffusion operator K as dilation operator acting on functions on $L^2(G)$

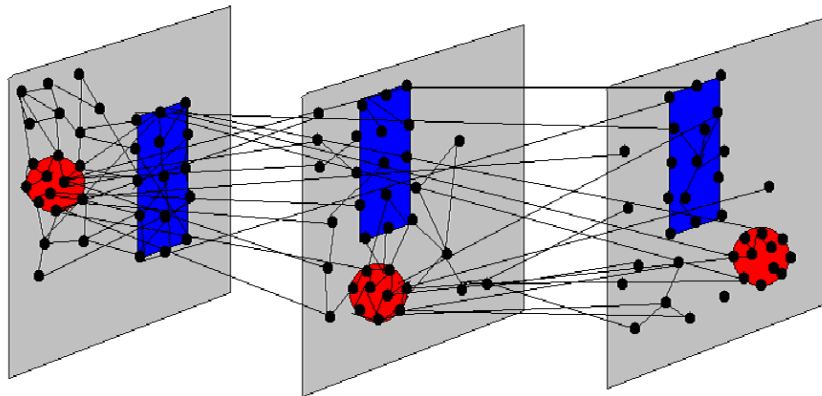
⇒ define multiresolution structure via dyadic powers of K : K^{2^j} , $j \geq 0$

Recipe: Divide the spectrum (eigenvalues) of K into different ‘frequency bands’ and find orthonormal bases for the spaces spanned by the corresponding eigenvectors

⇒ [Multiresolution Analysis and ONB for functions on \$G\$](#)

3. Nonlinear Approximation of Spatiotemporal Data Using Diffusion Wavelets

- build a weighted graph G from the $3d$ image data



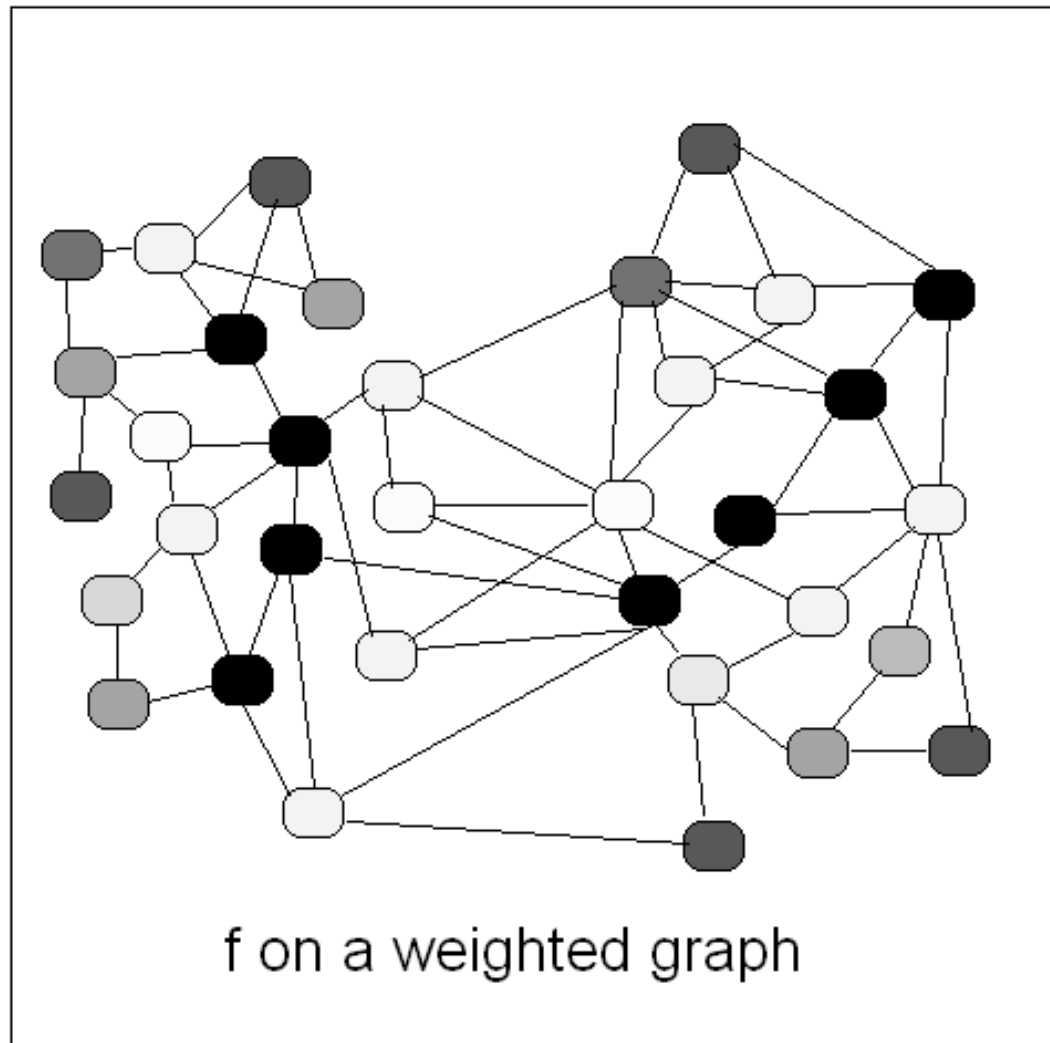
vertices: whole set of pixels, or due to complexity considerations: a subset (downsampled version of the sequences/ filtering/feature point selection)

edges and weights: difference of intensities, distance in space, feature point properties, information from a *motion prediction* or a combination of the above

function f on G : additional attributes on the vertices, for the 'pure' graph $f \equiv 1$.

\Rightarrow Encode local similarities in G

Result: abstract graph G from the data, $f \in L^2(G)$



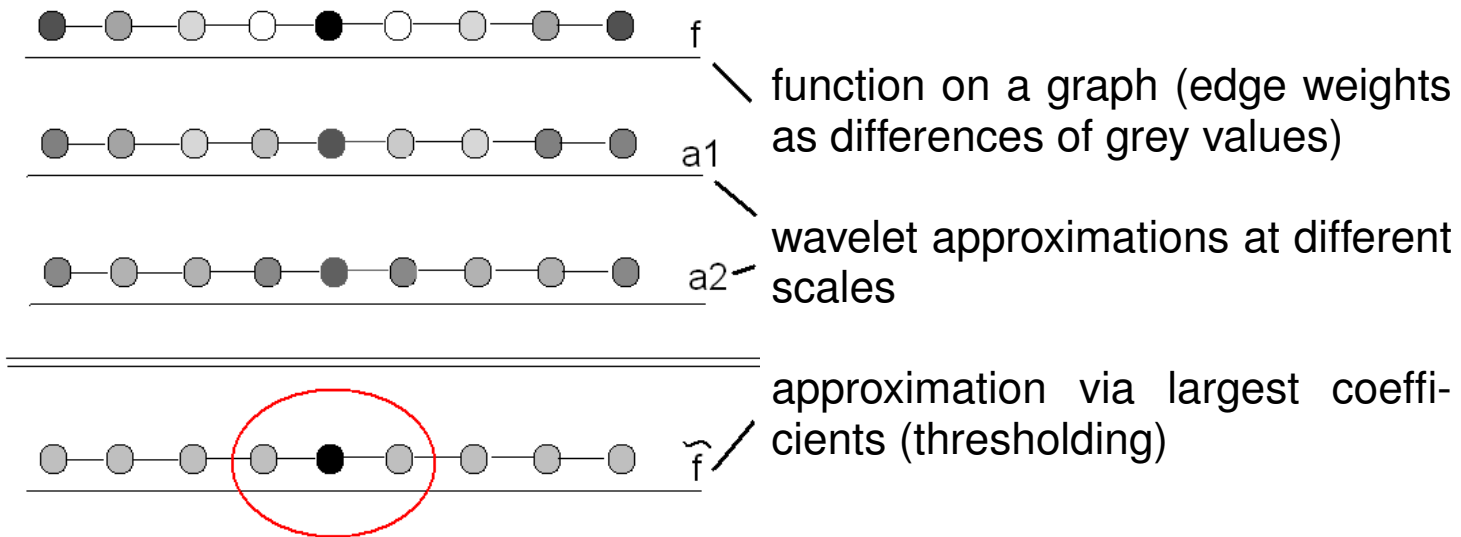
- Build diffusion wavelet basis $(\psi_{j,l})_{j \geq 0, l \in \mathbb{Z}}$ on G
- Calculate wavelet coefficients $(\langle f, \psi_{j,l} \rangle)$

\implies **Result:**

sequence of coefficients like in classical wavelet transform, **but:**
information encoded now defers to **structural similarity** of the data instead of
properties on the fixed grid \mathbb{R}

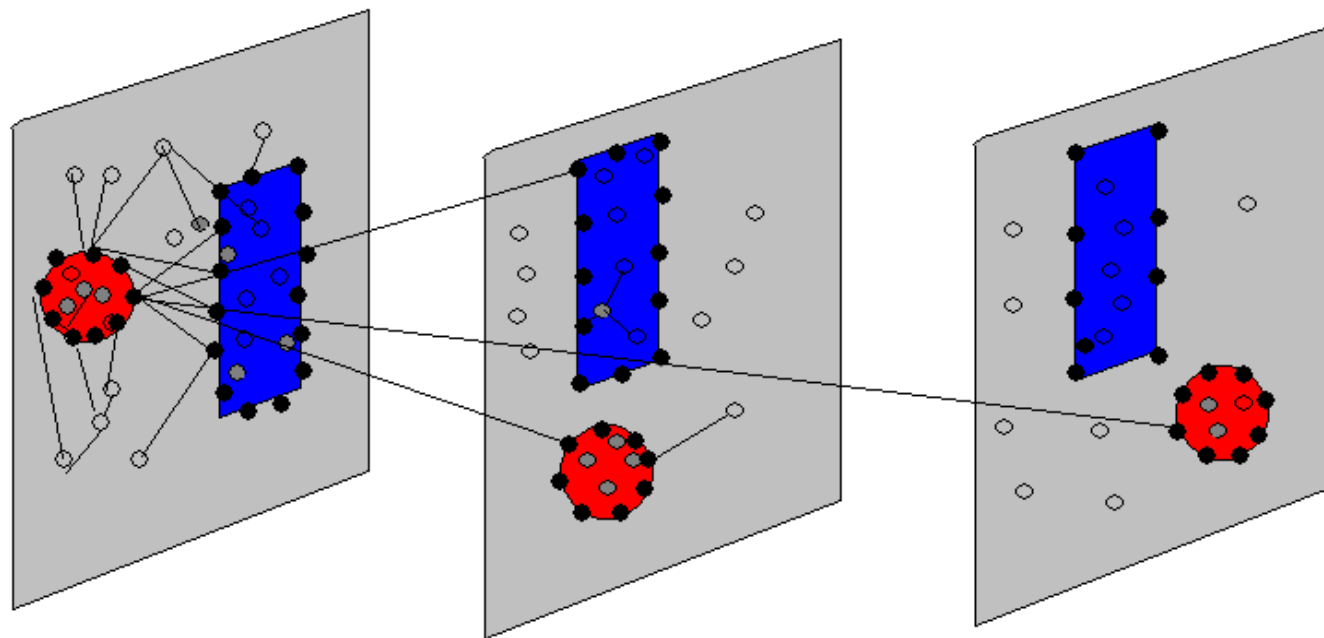
- Approximations on different scales available
- **Structure-preserving compression** via thresholding on the coefficients

Example



- Function is **smoothed** where local changes of the weights are small, where '**discontinuities**' (large weight changes) are **preserved**
- Remember: weights encode local similarities (intensities, motion properties)
⇒ **structure-preserving compression**

Structural approximation of the image sequence



4. Conclusion and Outlook Towards Spatiotemporal Segmentation with Diffusion Wavelets

- Diffusion wavelet bases lead to a **true multiscale decomposition** on a graph
⇒ Opens the door for a multitude of (graph based) CV tasks

Presented here as a first step:

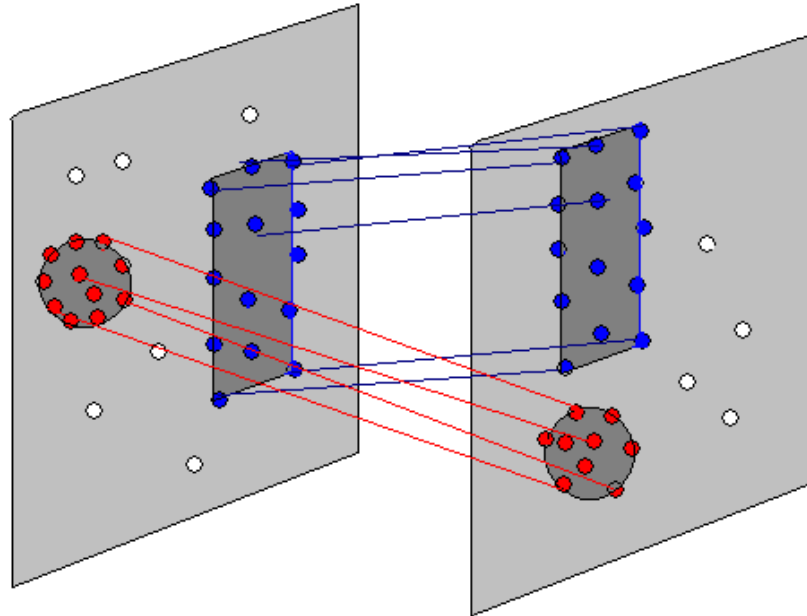
Algorithm for structure-preserving compression using diffusion wavelets

- derived from classical wavelet methods now lifted to a graph-based setting
⇒ theory relating properties of the function to the approximation error also available in this setting
- data smoothed by the approximation, abrupt changes in the edge weights (which can describe object borders in single images or the main direction of movement) are preserved
⇒ **Now** working on implementation and experiments

Next step:

- ⇒ **Future work:** spatiotemporal segmentation using diffusion wavelets (labelling of vertices via a HMM on the coefficients)

Outlook: Spatiotemporal Structural Segmentation



Segmentation by **labelling of graph vertices** (different colors),
Grouping by local similarities (intensities/motion profile/combined) via classifying diffusion wavelet coefficients across scales