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FWF P18716-N13

Nonlinear Approximation of Spatiotemporal Data Using Diffusion Wavelets

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Motivation

- Recent concept of **Diffusion Wavelets** (Coifman and Maggioni, 2006) allows construction of wavelet bases for functions defined on other than R^n, such as certain domains, manifolds and **graphs**
- **In this work**: study the use of **classical wavelet algorithms**, lifted to a **graph based setting**, concentrating on an algorithm for nonlinear approximation of **2d+time image data**

Introduction

- Diffusion Wavelets: particular instance of **spectral graph theory**
- In place of the usual dilation on R^n : **diffusion operator** on the data (given as a weighted graph) as **scaling tool**, dividing its spectrum (set of eigenvalues) into sets of different \`frequencies', obtaining a **multiresolution analysis** and an **ONB for functions on the graph**
- Diffusion Wavelet coefficients code **structural similarity** of the data encoded as a graph

$\longrightarrow$ Nonlinear approximation via thresholding on the coefficients just like in the classical wavelet algorithms (compression, denoising), obtaining a **structure-preserving** compression of the data

Outlook

- Nonlinear approximation on a graph: can be seen as a **first step towards structural spatiotemporal wavelet segmentation**
- In order to obtain a **true segmentation**: first idea is to use a Hidden Markov Model on the coefficient tree, classifying the coefficients as 'large' or 'small' and following them across resolution levels
- Segmentation method we work on: could be used as a way of a **combined spatial and motion segmentation** of a whole image sequence

$\longrightarrow$ instance of 'offline' tracking method (similar to the *normalized cut* tracking, involving a true multiresolution analysis on the data)

Algorithm

Input: image sequence (2d + time data)

Output: nonlinear approximation of image sequence

- Build a **weighted graph G from the image data**

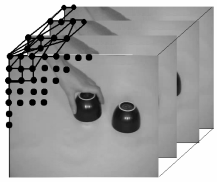
Vertices: whole set of pixels or subset (e.g. using a downsampled version of the sequences, by filtering or by a feature point selection procedure)
Edges and weights: encode the local relations between vertices, (i.e. difference of intensities, distance in space, feature point properties, information from a motion prediction or a combination of the above
Function f on G: additional attributes on the vertices

- build a **diffusion wavelet basis** for functions on G
- compute **coefficients** of f with respect to this basis
- hard or soft **thresholding** on the coefficients
- reconstruction

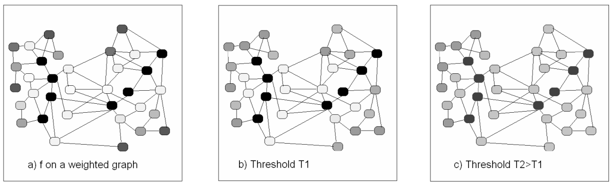
Example

Visualization of the algorithm by an example

1.Build a weighted graph from an image sequence



2.Obtain an abstract graph



a) f on a weighted graph   b) Threshold T1   c) Threshold T2>T1

3.Thresholding of graph wavelet coefficients

Experimenting with different choices of vertices, weights and thresholds on real data will be part of our future work

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